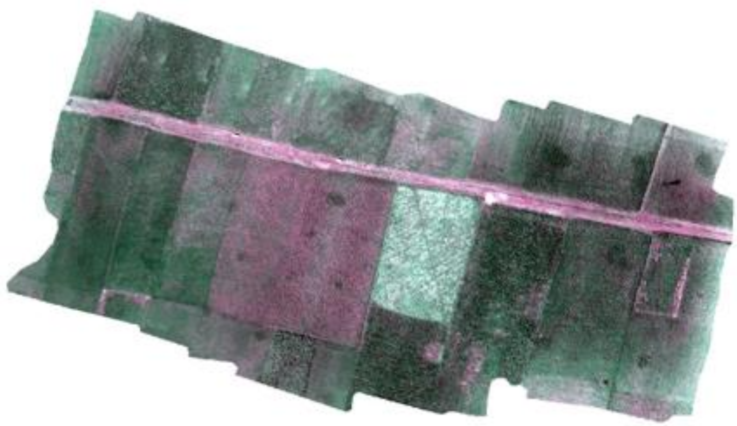
ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

REMOTE SENSING AND GEOINFORMATICS

Crop Field Classification using fusion approach of Unmanned Aerial Vehicle (UAV) and Sentinel 2A satellite data: the case of Oda Dhawata Kebele Cluster farmland, Oromia Region, Ethiopia



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REMOTE SENSING AND GEOINFORMATICS STREAM

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Declaration,

I hereby declare that this thesis represents my own work, has not been done for a degree or master's degree, diploma or in any other qualifications from university and that all sources of materials for thesis used have been acknowledged.

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Abbreviations

GS	Gram Schmidt
MS	Multispectral
UAV	Unmanned aerial vehicle
UAS	Unmanned aerial system
S2A	Sentinel 2A
3D	3Dimensional
2D	2Dimensional
DSM	Digital surface model
DN	Digital number
RF	Random forest
NDVI	Normal Difference Vegetation Index
GNDVI	Green normalized difference vegetation index
NDRE	Normalized Difference Rededge
NIR	Near infrared
TIR	Thermal infrared
SWIR	Shortwave infrared
OA	Over all accuracy
ATP	Automatic tie points

Abstract

Remote sensing technology has played a significant role in the dynamic information extraction of crop information and mapping. The accuracy of crop type information using this technology needed ground truth data and high-resolution data set. However, accurate crop classification remains challenging in both the same crop with different spectral and different crops with same spectrum phenomenon in the field. Now days, Unmanned Aerial Vehicle (UAV)-based high-resolution images gets the popularity for its high spatial resolution and applicability to solve scientific problems. Therefore, this study aims to evaluate the potential of UAV images for crop field classification blending with Sentinel 2A satellite images. In this study, Crop types was identified such as Teff, Wheat, Faba bean, Barley and Sorghum. UAV data, sentinel 2A and fieldwork data were acquired. The UAV data was preprocessed like camera calibration, photo alignment, dense point cloud generation based on the estimated camera positioning of scouting crop types. Then, orthomosaic UAV image was generated from single dense point cloud. UAV data was fused with Sentinel 2A (the medium resolution) satellite data using Gram Schmidt pan sharpening method to improve the spectral variability and evaluating the accuracy of crop type classification. For crop classification, machine-learning algorithm on R software was applied using the Random forest (RF) and Maximum likelihood. The vegetation indices of the NDVI for UAV and S2A was carried out and correlation was performed. The results show that RF classifier algorithm classifies the crop types with 94% overall accuracy whereas the Maximum likelihood classified with 90% overall accuracy. The correlation between the vegetation indices shows the fusion of UAV and S2A for crop type classification was 0.57. This indicates that how much the fusion of the sensors was fine for classifications. It is mostly significant that if the area of interest enhanced then easily detect the regions stressed, monitor and crop type mapping of Ethiopian Agricultural practices using blending of UAV and newly satellite launched by Ethiopian.

Keywords: UAV, Sentinel 2A, fusion, Random forest, maximum likelihood and crop type classification.

Chapter One

1. Introduction

1.1 Background

Over the past decades, nice efforts are taken to develop multiple ways for crop classification mistreatment completely different remotely sensed data and LULC Remote sensing product. Previous studies centered typically on crop composition surveys and also the classifications with the low spatial resolution (Moderate Resolution Imaging spectro-radiometer, Advanced Very High-Resolution Radiometer) and medium spatial resolution data (Landsat, Sentinel, Thematic Mapper, Enhanced Thematic Mapper) (Gao, 2015).

In recent years, remote sensing technology has a major role in dynamic data extraction of crop information and crop distribution mapping (Zhang Jiankang et al, 2012a). Satellite remote sensing information has the characteristics of enormous coverage area, short detection period, abundant data, and low value. It also provides new technical means for quickly and accurately getting crop types (Chen Zhongxin et al, 2017). However, the data for a given area at a given time cannot be suggested for more analysis because of the long period of high-resolution satellite re-entry cycle.

The accuracy of cropland area monitoring exploitation satellite remote sensing should be supplemented by ground truth data since it cannot meet the necessities. The application of remote sensing in agriculture is predicated on the concept of interaction of electromagnetic radiation with vegetation and crops material. It assesses the amount lightweight sunshine reflected from soil and vegetation; merely do not react to the quantity of transmitted and absorbed light. The application of remote sensing in agriculture has been applied since 1950s (Colewell, 1956). The image provided by satellite is of low-spatial and temporal resolutions as compared to UAV image is simply too insignificant result comparatively.

Accurate crops classification remains difficult work because similar crop with different spectral and different crops with same spectrum development within the field of agriculture. Recently, UAV-based remote sensing approach gains popularity not just for its high spatial and temporal resolution; however for its ability to get spectral band spatial data at the same time (Licheng Zhao, 2019).

Unmanned Aerial System, sometimes referred drone, Unmanned Aerial vehicle (UAV), Remotely piloted aerial systems (RPAS) are rapidly developing technologies that are used to collect data, such as digital imagery, pictures and videos using mounted cameras. The naming might be different in several countries. It is agreed that there is one difference between the UAV and UAS. UAVs are unmanned aerial vehicles in which it is just referring to the aircraft itself; while UAS refers to the ground control and communications units as a system. UAVs are a component of an UAS, which include a UAV, a ground-based controller, and a system of communications between the two (Newcome, 2004).

The emergence and development of UAV remote sensing technology has provided new ideas for gathering of crop information (Freeman et al, 2015a; Mesas-Carrascosa et al, 2014a; Rokhmana et al, 2015a). At low, medium and high resolution, UAV remote sensing will play a good role and might generate additional feasible crop distribution information that could be significant to the development and application of crop monitoring technology. Mapping of crop type using satellite image is challenging task due to complexities within cluster farmland field, and having similar spectral properties of different crop type. Recently sentinel satellite data launched with high resolution (10, 20 and 60), 13 spectral bands, and fast revisit time. UAV-technology is good choice for crop type mapping since its running comprises four spectral bands by these two systems.

Crop classification makes it possible to obtain the spatial distribution and planting area information of crops. A multiple crop mapping helps to show the dynamics of agricultural fields and may serve as the basis of crop structure adjustment and optimization to assist government decision-making (Asgarian, et.al, 2016). UAV has image composition with high resolution, simple operation, quick data acquisition and low cost. It can perform image collection for a certain area and combine ground data to quickly and accurately complete the crop planting information monitoring task. It can be used to complement to satellite remote sensing data' and aerial remote sensing, and provides accuracy verification for large-scale remote sensing (Del Pozo et al, 2014a).

Studies conducted on the crop type classification using drones, detection and mapping stressed crop and put forward many approaches and methods such VegNet (Vegetative-Network)-segmentations, canny-edge detector, dilation, gap-filling, and image extraction (Srivastava,2019).

So that high-resolution images provided by UAV were used in different studies for examination of crop health including Indices and monitoring. Vegetation Indices influences two properties of crop, i.e. Evaporation and photosynthesis (Warren and Metternicht, 2005).

Nowadays, UAS are changing the game in application of remote sensing (RS) in the agricultural sector by making data capture more affordable and timely accessible for applications for understanding the plant health monitoring. The need to know about farm plot/field plays a major role in piloting and implementing drone-based services. Use of UAS in precision agriculture is boosting day by day (Bansod, et.al, 2017). UAS role in agriculture are becoming important systems to collect data for precision agriculture and improve sustainability, efficiency and productivity of the agricultural practices. UAS help precision agriculture through helping variable rate mapping, and guide targeted farm management activities.

The important feature of precision agriculture (PA) is water stress management, crop health monitoring, including insects, nutrients, biomass, etc. (Bansod, et.al, 2017). The high and flexible spatiotemporal resolution makes UAS potentially affordable and important system for agricultural application. Most agricultural activities are influenced by spatial and temporal variabilities. Hence, agriculture needs large volume of spatiotemporal data to capture the highly varying spatial and temporal agricultural production factors. As the future trend is to move to precision agriculture, cost, labor and time efficient technologies for the agriculturally data collection and analysis systems need to be in place.

These days, varieties of innovative digital technologies are being widely introduced to sustain and improve agricultural production. One of the rapidly developing technologies with a huge potential to help in improving agricultural decision-making is UAV. As the future of agriculture is towards smart farming, integration of technologies like UAV-based data is becoming crucial for the use in precision agriculture. UAS helps PA through its variable rate mapping, and guide targeted farm management activities. UAVs are changing the game in application of RS in the agriculture sector by making data capture more affordable and time.

In this study, crop field classification using blending of Drone and Remote sensing data (sentinel) is one of the newest technologies and classic research topics in the scientific community of remote sensing, was applied for crop field classification.

1.2 Statement of the problem

The potential application of UAS for agricultural research and developments are enormous. So far, there has been lack of a feasible and affordable data acquisition means at farm level for agricultural researchers, experts and farmers to make the appropriate management decisions for agricultural practices and technology scaling. To properly and accurately map the agricultural landscape crops in the area, it is necessary to use the satellite technology. However, it is still challenging because i) agriculture area highly complex for mapping crop types. ii) Different crop types have high variability in phonological stages within cluster fields, which might lead to same spectral signature at some point of their progress. That is, accurately detect and discriminate between crop types and co-existing crop pattern/classification are problematic. Therefore, Unmanned Aerial Vehicle is the best alternative that need to fill such gaps because of its new technology and move on to the targeted area where we needed for the study manually. The study area comprises different crop type like Teff, wheat, Faba bean, sorghum and barley and the cropping system in the country is common, and it has been labor practices in every fragmented land as well. Complexity of mixed cropping and challenge for crop classification using normal approach of UAV and /or satellite data was not known yet. Therefore, since the technology is new coming the appropriate use of drone for detecting and mapping crop stress, monitoring and early advisory service is the most functionality of UAV.

1.3 General Objective

To evaluate the potential of fusion approach Unmanned Aerial Vehicle (UAV) images and Sentinel 2A imageries for crop field classification.

1.3.1 Specific objective

- Evaluating the UAV data for crop classification and mapping
- Mapping of farmland using Sentinel 2A satellite image
- To understand the potential of fusion approach of UAV and Sentinel 2A images for Crop classification.

1.4 Significance of the study

The research focus of this study is to use of UAV and fusion of satellite data specially within the newly –launched satellite sentinel 2A and almost high resolution to classify crop types of the farmland. The low spatial resolution of remote sensing and NDVI were not suitable in a complex Agricultural area like Ethiopian Agricultural farming system. This imagery cannot adequately capture the complex agricultural landscapes and farming systems of Ethiopia, which is among the most complex and fragmented Farming practices are considerably different in the country, where many farmers grow multiple crops with similar plant cycles and where intercropping is also common practice. The different farming practices all requires for the use of higher spatial resolution satellite platforms. Therefore, it is difficult to access satellite imagery which higher spatial resolution to address the specific problems, which characterize such complex farming practices. Therefore, UAV is the appropriate to use it and fuse within the image product of Sentinel 2A that it improves its spectral aspect. This research will explore selected potential applications of UAV. First, the research will focus on testing and demonstrate how UAV can contribute to a variety of fields by generating and providing UAU images (Orth mosaics). This initial UAV exploration will help to practice and identify potentials and limitation before starting to full application studies. Then after, varieties of agricultural use cases will be tested. The UAV image acquired is fused within Sentinel 2A data of the same area of interest, this very significant to upgrade the lower spatial resolution and spectral aspect of sentinel 2A Following this, it is intending to develop methods/models/ that align with other research aspects. Furthermore, to aware and expand the use of UAV data in the agriculture sector, it also requires on demand provision of continuous advice, support and training on the operation and application of UAV-based data.

Chapter Two

2. Literature Review

2.1 Remote sensing and Electromagnetic spectrum

Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft). Special cameras collect remotely sensed images, which help researchers "sense" things about the Earth. Some examples are: Cameras on satellites and airplanes take images of large areas on the Earth's surface, allowing us to see much more than we can see when standing on the ground, Sonar systems on ships can be used to create images of the ocean floor without needing to travel to the bottom of the ocean and Cameras on satellites can be used to make images of temperature changes in the oceans.Reflected energy describes how utilizing sunlight as an energy source causes some that energy to reflect or recover into space to be received by the sensor.

Electromagnetic radiation or EMR is the term used to describe all of the different types of energies released by electromagnetic processes. Remote sensing technologies rely on a variety of electromagnetic energy. Sensors detect and measure electromagnetic energy in different portions of the spectrum. Consequently, the huge wavelengths are classified into regions or spectral bands that are unit organized within the spectrum, which is shown in (figure1.1) shorter wavelengths (Gamma or x-rays), have a better frequency than longer wavelengths (microwaves or radio waves) and thus have higher energy content (Chueca, 2016)

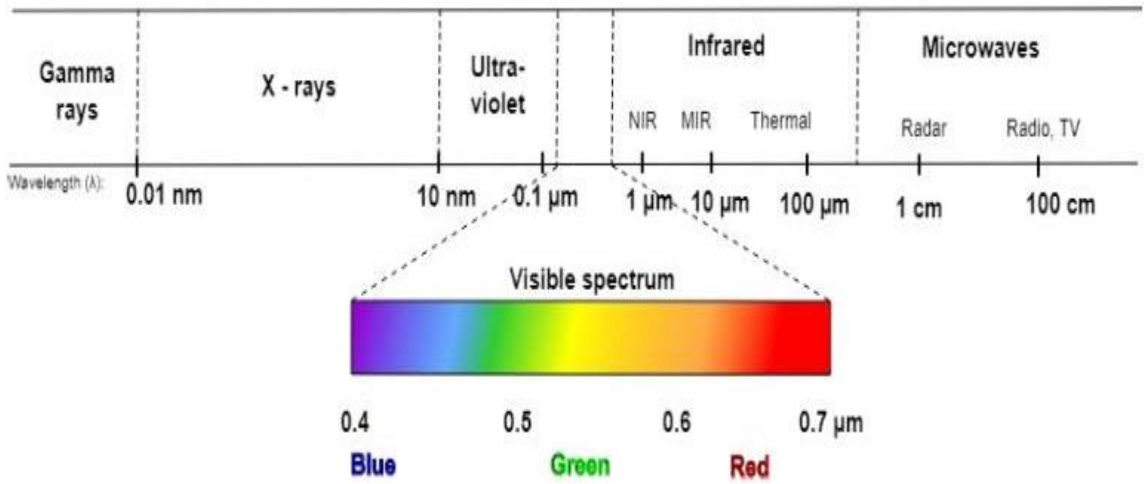


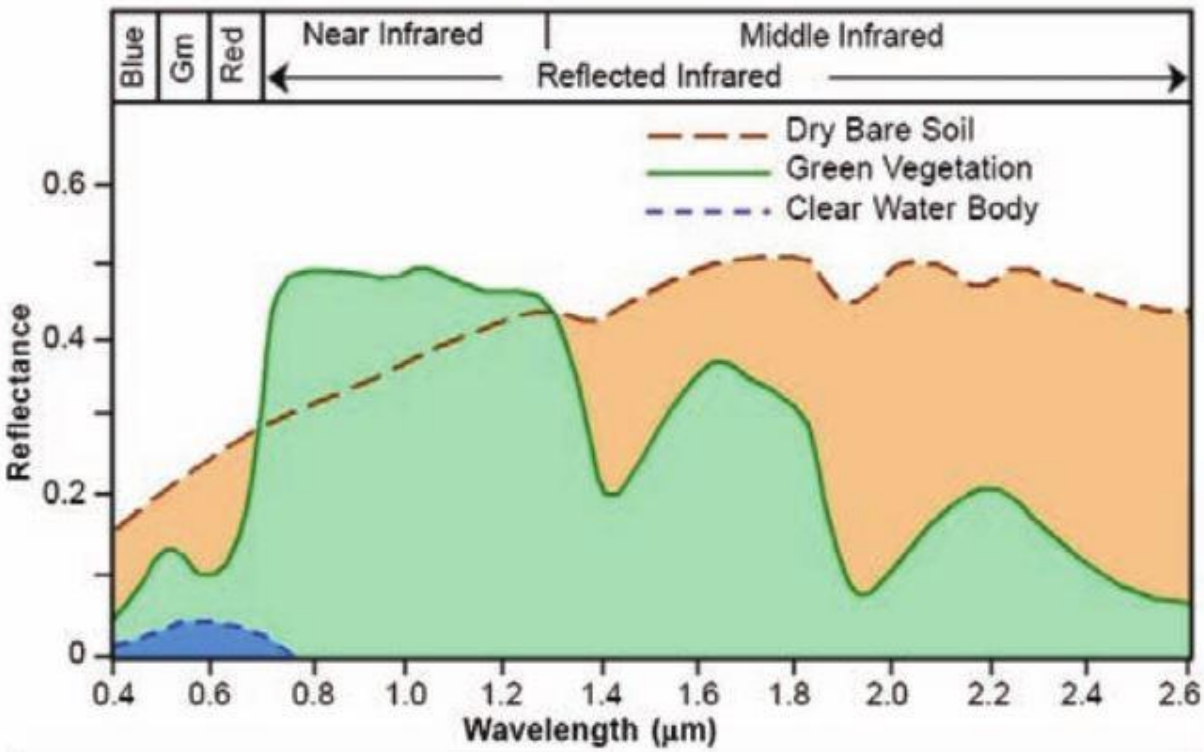
Figure 2.1. Spectrum and its spectral band division

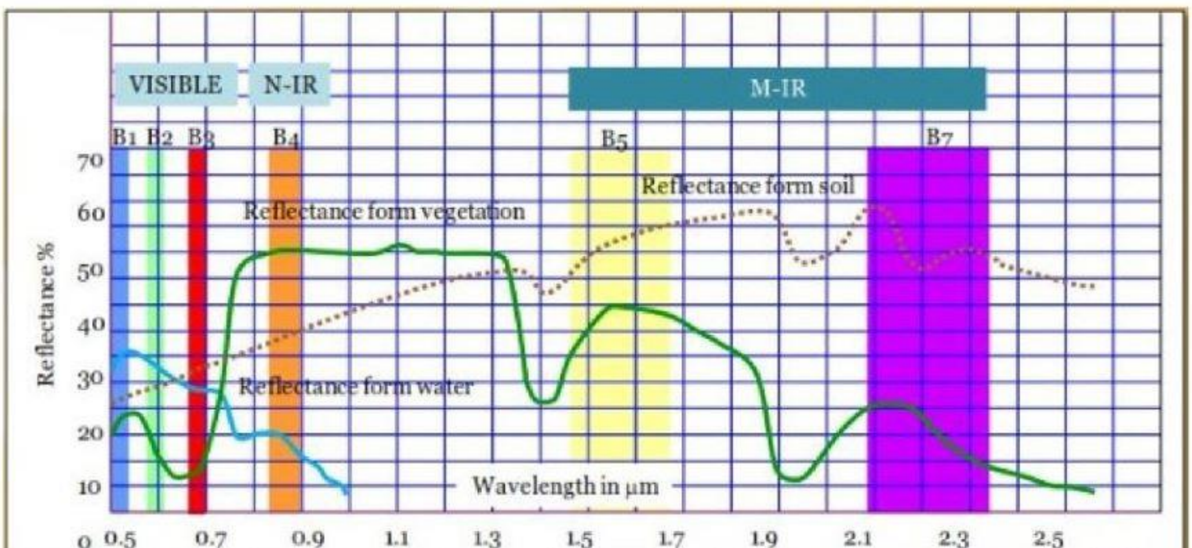
The visible and infrared bands are usually used bands in case of UAV platforms. The spectrum ranges from 0.4 to 0.7 micrometers and should be any divided into blue (0.4 -0.5 micrometers), green (0.6-0.7micrometers) and red 0.6-0.7 micrometers) bands. Because the name suggests, the visible band outlines the ranges of the spectrum that human eyes can sense. The non-visible infrared band ranges from 0.7 to 0.14 micrometers and may be divided into near infrared (NIR), short wave infrared (SWIR), and thermal infrared (TIR) bands (Chueca, 2016).

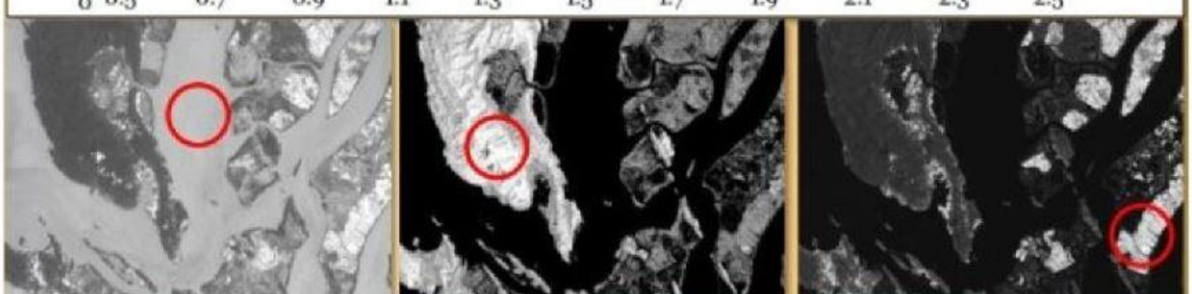
However, electromagnetic energy is reflected, absorbed or emitted across the various spectral band is ruled by the bottom surface and the way it reacts to completely different energy levels. Moreover, the land cover type as well as its physical and chemical properties control how the reflectance act across the electromagnetic spectrum.

2.1.1 Spectral reflectance of surface features

The spectral signatures produced by wavelength dependent absorption provide the key to discriminating different materials in the image of reflected solar energy. The property used to quantify these spectral signatures is called spectral reflectance: which is the ratio of different materials that can be measured in the laboratory or the field, providing reference data, which can be used to interpret images. As an example, the below figure shows contrasting spectral reflectance curves for three very common natural materials: dry soil, green vegetation, and clear water.







TM Band1: High reflectance in water TM Band4: High reflectance in vegetation TM Band7: High reflectance in Bare soil

Figure 2.2 spectral reflectance of surface features

The reflection factor of dry soil rises uniformly through the visible and near-infrared wavelength ranges, peaking within the middle infrared range. Green vegetation terribly a completely different spectrum. Reflection factor is comparatively low in the visible range, however it is higher for green light than the red in visible wavelengths is due to selective absorption by chlorophyll. The fore most noticeable feature of the vegetation spectrum is that the dramatic rise in reflection factor across the visible near-infrared boundary, and high near-infrared reflection factor. Infrared radiation penetrates plant leaves and is intensively scattered by the leaves' advanced internal structure leading to high reflection factor. The dips within the middle infrared portion of the plant spectrum square measure due to absorption by water. Dip clear water bodies effectively absorb all wavelengths longer than the visible vary, which ends up in terribly low reflectivity factor for infrared radiation.

Table 1. Surface feature reflectance comparison

Surface category	**Low reflectance**	**High reflectance**
Water	NIR (Near-infrared)	Blue(visible)
Vegetation	MIR (mid-infrared)	NIR(Near-infrared)
Soil	Blue (visible)	MIR (mid-infrared)

2.2 Remote sensing application in Agriculture

In recent years, remote sensing technologies complete a job in dynamic data extraction of crop areas and crop distribution mapping (Zhang Jiang Kang et. al, 2012a). Satellite data has the massive coverage of the area, short detection period, abundant data, low price and provides new technical means that quickly and getting accurately regarding crops type (Chen Zhongxin et. al, 2016a). However, because of the long period of high-resolution satellite re-entry cycle, the data for a given area at a given time cannot be guaranteed. The accuracy of cropland space observation exploitation satellite remote sensing cannot be meet the wants and should be supplemented by ground sample surveys knowledge exploitation ground sample data. Survey data to calculate the deduction coefficient of linear and fine options, to realize the fine extraction of crop planting areas extracted by remote sensing.

Remote sensing has emerged as a good and necessary supply of Land use information permitting developing and producing a land cover classification for both giant and tiny areas of various landscape characteristics .it has been used with success for crop mapping (Vyas et al., 2005, Conrad et al., 2010, Asgarian et al., 2016, Vuolo et al., 2018).

However, agriculture landscapes have a complex and extremely dynamic land use pattern, that is difficult to accurately classify using medium spatial resolution data (Asgarian et al.2016). The landscape is characterized by fragmented, little parcel-sized fields and different crop types within a pixel as well as completely different crop cover. Besides, there are diverse spatial and temporal variations between each crop type within moderately short time intervals (Immitzer et al., 2016). This dynamic character of the agricultural landscape have a challenge to agricultural land use mapping. The advent of unprecedented satellite-based imaging technology provides multi-temporal data that possess regular revisiting intervals and weather independent acquisition capabilities has made the mapping of crop kind dynamics manageable (Li et al., 2014).

Crop kind mapping was historically carried out using a field-based survey. However, census and also the ground-based survey are not feasible in an exceedingly a large-scale agriculture landscape as it is laborious, expensive, vulnerable to errors, and time-consuming hence the use of timely, less costly, and quicker ways of crop mapping has become a necessity (Ouzemou et al., 2018). The remote sensing imagery is vital in enhancing broad-scale agronomical management and inside field monitoring such as precision agriculture.

2.3 Use of multispectral data for crop Diversity Mapping

The conventional methods for crop types mapping such as field surveying have become laboriously expensive bringing in the necessary to use economical, affordable, and synoptic ways such as remote sensing (Ouzemou et al., 2018). Remote sensing technology has been known to proverbial to produce cheap and correct means of collecting agriculture land information required for crop type in fragmented land structures. Multispectral and multi-temporal remote sensing knowledge are generally employed in the past few decades for crop identification and crop mapping (Vyas et al., 2005, Conrad et al., 2010, Veloso et al., 2017, Ouzemou et al., 2018) since they are believed to supply prime quality and affordable source of data that allows land-use dynamics to be detected and assessed at a much finer spatial scale, particularly crops (El Hajj et al., 2009).

The ability to separate or discriminating one crop from another accurately depends on a unique spectral signature that every crop or Land use kind reflects on the electromagnetic spectrum (Schmedtmann and Campagnolo, 2015). However, there is a limitation related to mapping crop types and discriminating them from the co-existing land uses like parcel-to-parcel variability of the plant reflectivity of identical category and spectral similarities the co-existing Land use and crop types (Schmedtmann, 2015). Consequently, it is necessary to differentiate between the crop types spectral characteristics hence multispectral data has become the most common choice for crop diversity mapping. This is due to the high spatial resolution of both data acquisitions of UAV and sentinel 2A

2.4 Unmanned Aerial Vehicle (UAVs)

Unmanned Aerial vehicle is a low-price various in sensing technology and knowledge analysis techniques in recent years. Remote sensing victimization magnetism to see the properties of a targeted object from a distance and has the advantage of extensiveness, non-invasiveness, timeliness, and adaptability. In line with Thomasson (2011), some early studies victimization satellite pictures for soil surveys and soil mapping were done, however, the pictures were typically unable to produce quantitative data regarding specific soil properties. Thus, UAV will be the applicable choice to collect accurate data in the field .it had been known as possible technology which will be generate high spatial resolution imagery (<1m) and at a temporal frequency applicable within the production of actionable information about crop and field standing (Elarab, 2015).

The most advantage of UAV,it will capture the pictures of the farmer's cropland by travel the drone on the plots of the crop with a range of camera filters that give the farmers with multispectral imaging, enable the image process and analysis which gives better information on their crop's health and progress at equivalent time, distinctive space coverage of the crop varieties that need special attention. Because technology is new, the various application potentials of the information and therefore operations of UAS has to be practiced through piloting, explored and adapted in the Ethiopian context. To accumulate numerous agricultural information and generate actionable information, it needs developing operating methodology on the employment of UAS knowledge for agricultural analysis and development functions. The most drawback in UAS is that also there is no standardized workflow for the use of UASs in such applications, because it may be a comparatively new space (Tsouros, Bibi, & Sarigiannidis, 2019). There are still several progress and quality problems caused by UAS: there is additionally the part of cameras and their resolutions and software considerations, which are a necessary contributor to good data quality (FAO, 2018). Unmanned Aerial vehicles carrying imaging payloads are frequently used for remote sensing applications to accumulate high-resolution pictures for watching numerous aspects of agriculture and the environment. Progress created within shrinking and reduction in the price of sensors, Global position systems (GPS) devices, and embedded computers have enlarged the chance of remote sensing victimization business off-the-track (COTS) UAVs (Diaz-Varela et al., 2014). The two most vital characteristics of UAV platforms are said to be terribly high spatial and temporal resolution they support, which permit recognition of events occurring at neighborhood scale during specific time window (Michez, Piégay, Lisein, et al., 2016). These benefits build UAVs feasible for watching crops in intimately, capturing necessary synchronic linguistic stages for Precision Agriculture,that may be classic limitation of ancient remote sensing platforms. The flexibleness in acquisition times and therefore the low price of operation could exceed the demand from ancient manned aircraft and different platforms like WorldView-2, WorldView-3, GeoEye-1, IKONOS, Quick bird, and Rapid Eye.

The recent and rapid growth of UAVs in environmental and agricultural applications has prompted the event of innovative technologies. Several studies was conducted victimization of UAVs to assess the potential pictures to support precision agriculture. Lelong et al. (2018) assessed UAV imagery for watching a wheat crop in tiny plots. Ballesteros et al. (2014b) examined the link between green canopy cover and leaf area index to characterize crop growth. They allow over that high-resolution images obtained with UAVs, beside correct treatment, may be a useful tool for precision monitoring of crop growth and development, and has the potential to advise farmers on water necessities, yield prediction, and weed and insect infestation, among others. Stroppiana et al. (2015) tested the correlation between reflectance in the spectral channels and vegetation indices derived from imagery acquired with a multispectral sensor onboard a UAV to estimate rice yield. Their results suggested that UAVs are a potential platform for knowledge acquisition for crop watching.

2.4.1 Guidelines recommended about Parrot blue grass (Drone application for precision agriculture) in Ethiopian Institute of Agricultural Research (EIAR)

Parrot Bluegrass is specifically designed for agricultural functions, crop mapping, and analysis that may quickly provide actionable data to farmers, researchers, ensures, and anyone else who works directly within agriculture. In recent years, there has been robust activity within the questionable precision agriculture, notably within the watching aspect not only improve productivity however additionally crop diversity mapping at farmland so that Ethiopian Institute of Agricultural research is meant to use this technology then address such gaps at the country level for Agriculture sector. Initially, very different consultants are trained to manage the drone-like Piloting, analysis, interpretation, and agronomists are trained and licensed. Parrot fields associate degree an end-to-end agriculture drone answer, that provides farmers, agronomists, and researchers with the insight t need to boost the standard of the crops and maximize yields. Overall, Parrot Bluegrass plays a good role in image classification, works fine in Agricultural farm mapping. Even during which inaccessible areas and sensible monitoring tool that eases data collection and the correct result provides. Thus, EIAR is incorporates accountable establishment institution that escapes the agricultural farmland mapping, monitoring crops, early advisory to the end-users i.e., farmers at national by using these techniques.

2.5 Crop Diversity mapping using UAV data

UAV is that the most vital technology that supports the term preciseness agriculture that is however, farmers will manage their crops to form certain, if there is enough offer of fertilizers and water, monitor progress, quality and maximizes productivity and yield. Additionally, these it will predict pest spot areas and management, saves fertilizer spray to whole farmland to tackle unwanted flood and/or pests and additionally farmers will understand the crop diversity within the plot of areas so classify consequently inside the cluster of farmlands, determine the crop kind largely dominated. Thus, the usage of UAV will enable farmers to constantly monitoring their crops' condition by air to find out problems quickly and at similar time reduce time consumed for ground-level spot checks. For example, a farmer may notice through time-lapse UAV photography that part of their crop is low in nutrients or not well irrigated in some areas that are difficult to access quickly.

Agricultural crop productivity are suffering from many factors like soil moisture, nutrients, water holding capacity, PH, and others (letter, 1958). To cope up with the higher than factors, farmers use advanced techniques like fertilizers, manures, irrigational facilities to extend the yield and avoid crop loss (Yadav, 1998). Therefore, the farmers have to be compelled locations of stressed regions so they will appropriate remedial actions whereas several government want this data to predict the longer term crop costs, to estimate crop injury, and the financial firms and insurance companies need these data to analyze the crop damage due to cyclone, drought and flood to pay for insurance compensation (Deloitte, 2019). Farmers will understand and the corrective measures which require to be taken to ensure a highly productive crop. The current systems use satellite knowledge for the gathering of the information that is extremely costly and has low resolution; additionally, this knowledge are limited to some scientific organizations only. However, with the utilization of drones, this data are easily accessible to everybody .Therefore increasing the accessibility of the technology whereas ensuring high-resolution images. Therefore, the drone is preferred rather than satellite for this purpose.

Nowadays, associate degree increasing variety of unmanned aerial vehicles (UAVs) provide the choice to acquire very high-resolution (VHR) data with such systems.it is potential to flexibly record data in an optimal resolution. For agricultural mapping of small-scaled fields' spatial resolution between 0.5m-3m is recommended to assess the piece of land variability (Atkinson, 1997). The everyday application fields of UAVs comprise vegetation, environmental, urban, or disaster monitoring (planes, 2015), additionally as preciseness agriculture, land cover mapping, and rangeland monitoring in the agricultural sector (Shahbaz, 2014). VHR data derived with UAV have been used to determine land cover of small agricultural areas up to a few square kilometers (Ahmed, 2017) Constraints are imposed by weather (e.g., rain and wind) and unfavorable solar illumination conditions. However, since UAVs are usually operated at low flight altitude, data acquisition is additionally potential beneath cloudy conditions. In some countries, legal restrictions for operative UAVs apply (colomina, whitehead: 2014, stocker, 2017). Apart from that, UAV data acquisition is a lot of versatile throughout the day and not restricted by given revisit times, as in the case of satellite, or potential flight restriction with the larger airborne platform.

2.6 Sentinel 2A data

Sentinel 2 will carry on optimal instrument payload that will sample 13 spectral bands: four bands at 10m, six bands at 20m, and three bands at 60m spatial resolution. The orbital swath width will be 290km. Sentinel 2A is a satellite sensor launched on 23 June 2015 by the European Copernicus program that provides a geographical information in areas of land monitoring, emergency management, and security. Data can be modified and adapted by users interested in thematic areas such as mapping of land cover, classification and change detection, as well as forest management, water management, monitoring of vegetation, agriculture and food security and provide complementary knowledge to mission like LANDSAT, SPOT-vegetation and ENVISAT/MERIS sensor. Sentinel 2A could be a polar orbiting, sun-synchronous mission that gives systematic international coverage of land surfaces, between latitudes 56^0 south and 83^0North likewise as observation of upcountry waterways and coastal areas.

Table 2. Spectral bands and spatial resolution of Sentinel-2A

Spatial resolutions bands	Band Number	Band name	Central wavelength(nm)	Band width(nm)
10m	2	Blue	490	65
	3	Green	560	35
	4	Red	665	30
	8	NIR	842	115
20m	5	Red Edge	705	15
	6	vegetation red Edge	740	15
	7	vegetation red Edge	783	20
	8a	vegetation red Edge	865	20
	11	SWIR-snow /ice/clouds	1610	90
	12	SWIR-snow /ice/clouds	2190	180
60m	1	coastal aerosol	443	20
	9	water vapor	945	20
	10	SWIR-cirrus	1375	30

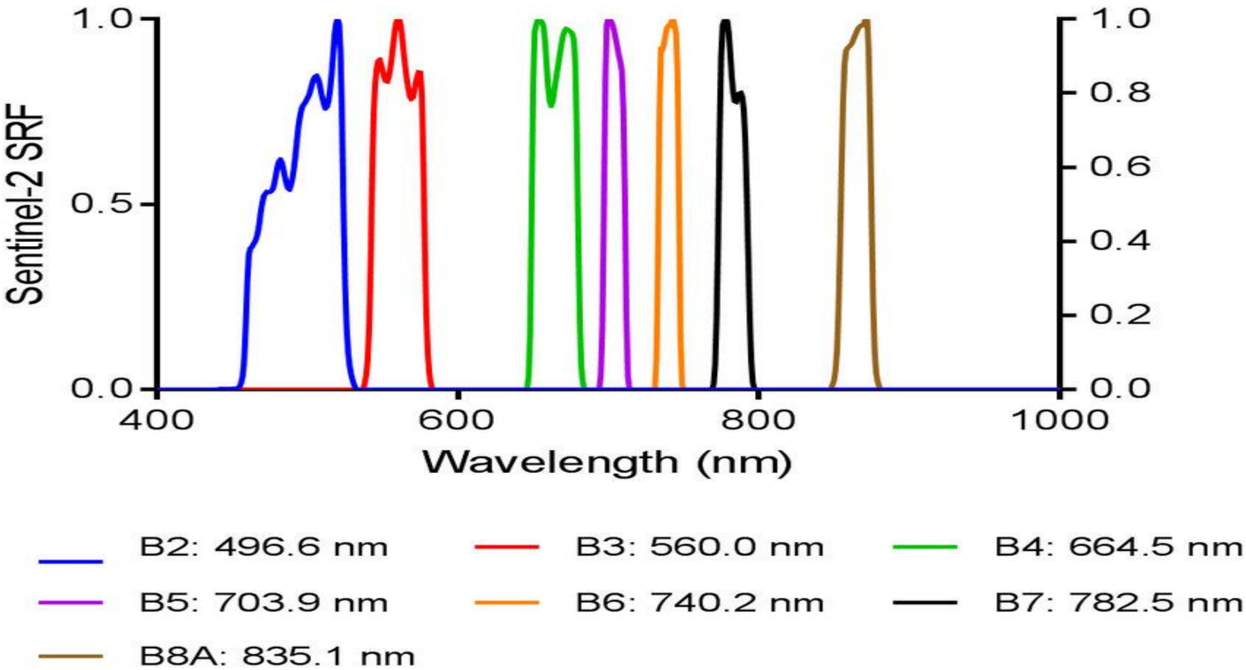


Fig 2.3. Spectral response for the Sentinel-2A Multispectral Instrument sensor modified from (ESA 2016)

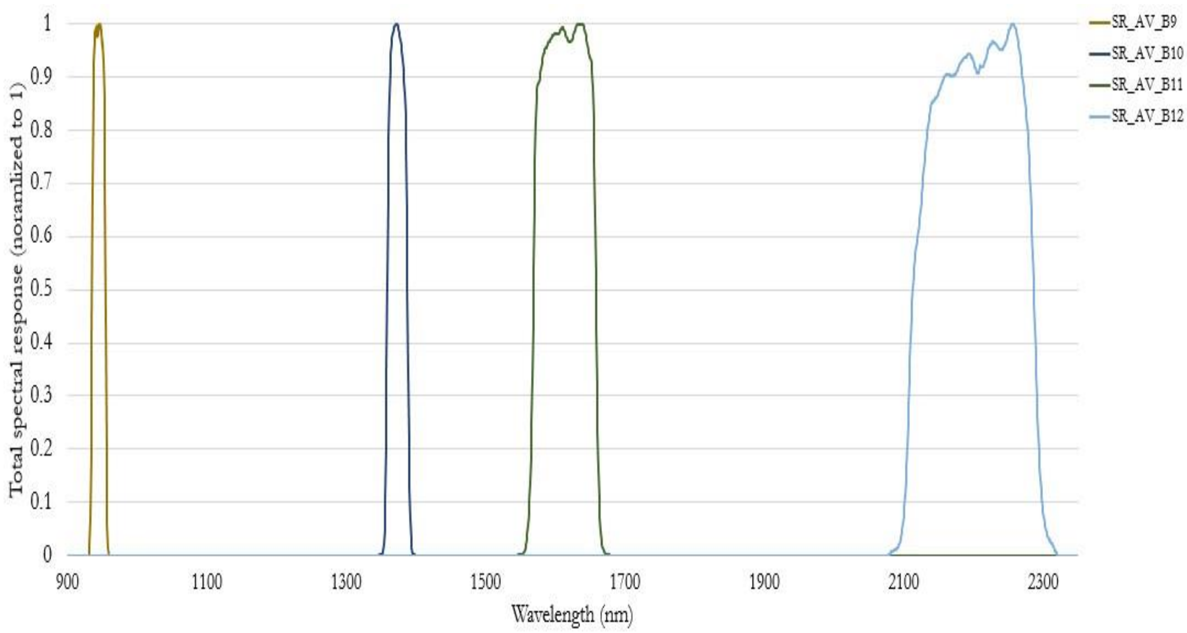


Figure 2.4 Sentinel-2A spectral response average – SWIR

2.7 Crop Diversity mapping using sentinel 2A data

Crop diversity identification is incredibly necessary within the agricultural sector. In order that most studies conducted regarding Landuse, land cover classification whereas crop type classification using satellite product were rare. Thus, sentinel 2A is the most high-resolution satellite data among satellite data products; it detects crop diversity /type identification during this study. Crop area extent estimates and crop type provide crucial data for agricultural observation and management. Remote sensing imager general, and, in particular, high temporal and high spatial resolution of 10,20, and 60m over 13 spectral bands in the visible, near infra-red, and short wave infra-red part of the electromagnetic spectrum (Malinovsky et al.,2012). The four bands that have 10m resolution (blue, green, and near infra-red) modify compatibility with SPOT 4 and 5(Taona,2019) and six bands at 20m resolution assist in the level 2 parameters for image process (Drusch et al.,2012).The remaining bands at 60m are for atmospheric corrections (aerosols retrieval)and cloud screening (cirrus detection) (Drusch et al.,2012), hence they allow spatial variability of atmospheric geophysical parameters to be sufficiently captured .the improved characteristics of the multispectral sensor meet the necessities for crop mapping because it has shorter revisit periods to cater for the temporal dynamics of crop growth at the side of medium spatial resolution over wide spectral channels enabling the discrimination of acute vegetation spectral signatures. Bearing in mind that the satellite has been recently launched, studies to analyze its potential for crop type mapping measure are still emerging. (Immiter et al., 2016), demonstrated the potential of Sentinel 2A data for crop types and tree species mapping and concluded that high spectral, spatial, and global coverages are the best in providing high classification accuracy. Thus, due to this implication Sentinel, 2A data is to establish the performance of data in mapping heterogeneous crop diversity within the field provided by the outstanding characteristics of this sensing element.

2.8 Multispectral Image Fusion techniques

Image fusion is to combine the higher spatial information of feature in one band with higher spectral information in another dataset to create ‘synthetic ‘higher resolution multispectral datasets and images.

$$\text{Pan} + \text{MS} = \text{Fused image}$$

This is to create the lower multispectral resolution, the sharper resolution and improved classification in fusion approach.

Multiplicative method: combines information sets by multiplying each element in every band of the MS information by the corresponding element of the pan-sharpened information (pohl. C, 1997). To compensate for the increased the brightness of values (BV) the root of the mixed data set is taken. However, this method has its own disadvantage that it Alters the spectral information of the first image.

Brovey method: since the first Brovey transform can only allow three bands to be fused, the transform has to be modified. The changed algorithm is a ratio where the information values of every bands of the multispectral data set are divided by the overall of the MS data group and then extended by the pan-sharpened data set. Its limitation was three bands at a time should be merged from MS data.

Wavelet method: The wavelet transform decomposes the signal based on elementary functions, the wavelets. By victimization this, a digital image is decomposed into a group of multispectral resolution images with wavelet coefficients. For every level, the coefficients contain spatial variations between two successive resolution levels. The disadvantage of this technique was poor directional selectivity for diagonal features, because the wavelet features are separable and real.

IHS method: Intensity hue saturation (HIS) separates spatial (intensity) and spectral (hue and saturation) information from atypical RGB image. The intensity refers to the overall brightness of the image, hue to the dominant or average wavelength of the sunshine causative the color and saturation to the purity color. The disadvantage is merely three bands concerned.

PCA method: The principal component analysis (PCA) could be a applied math technique that transforms a multivariable data set of related variables into dataset of unrelated linear combinations of the original variables. For, images it creates unrelated feature space that may be used for additional analysis rather than the original MS feature space The PCA is applied to the MS bands. The procedure to merge the TM and pan data using the PCA technique is comparable to that of the HIS technique. The TM data, either three or all six reflective TM bands, are used as input to a PCA procedure. The justification used for exchange the primary principal component image with the stretched pan data is that the pan data are approximately equal to the first principal component image. This assumption is made because the first principal component image will have the information that is common to all or any bands used as input to PCA whereas spectral information distinctive to any of the bands is mapped to the opposite parts (Chavez and kwarteng ,1989).

Gram Schmidt method: The Gram Schmidt (GS) process transforms a group of vectors into new group of orthogonal and linear independent vectors.by averaging the MS bands,the GS fusion simulates a low-resolution panchromatic band. Because the next step, a GS transform is conducted for the simulated panchromatic band applied as the first band. Then the high spatial resolution panchromatic band take places the first GS component. Finally, an inverse GS transform is applied to create the pan-sharpened multispectral bands (Sarp, Gulcan, 2014)

HP method: High pass filter fusion could be a method that make the high frequency components of high-resolution panchromatic image super imposed on low-resolution multispectral image, to obtain the enhanced spatial resolution multispectral image.

Ehlers method: It is based on an IHS transform coupled with Fourier domain filtering. The principal idea behind a spectral characteristic preserving image fusion is that the high-resolution image has to sharpen the multispectral image without adding new grew level information to its spectral components.To facilitate these demands, two pre-requisites have to be addressed. First, color and spatial data have to be identified. Second, the spatial information contents have to be manipulated in a way that allows an adaptive enhancement of the satellite images.

Subtractive method: uses a subtractive algorithm program to pan-sharpen multispectral pictures. Specifically, it had been designed for Quick bird, IKONOS and for mosaic images that have simultaneous acquisition of the pan and MS, with all four multispectral bands gift, and magnitude relation between the MS and pan image pixels sizes of roughly 4:1. Alternative sensors that have similar capabilities ought to conjointly work well with algorithmic program. The strategy is restricted to twin sensor platforms with specific band ratios between the high-resolution MS image.

Chapter Three

3. Data and Methodology

3.1 Study area and Materials

3.1.1 Study area

The study area is located in Arsi zone, which is called Oda Dhawata Kebele, known for Agricultural land with $8^0\ 1^{'}57.05^{''}$ N and $39^0\ 10^{'}39^{''}$ E (figure 1) latitude and longitude respectively. The diversified crop types were grown in the cluster of farmlands with suitable topography (flat) and good soil status. Crop types like Teff, Faba bean, barley, wheat and sorghum was grown on the demonstration site of the farm with a total area covering of 7.55ha. The average temperature ranges 10-25 ^{0}c. Its altitude ranges from 500 to 3000 masl. Over all, Arsi Zone including this study area receives rainfall twice per-year (belg and meher) and on average receives from 800-1200mm.soils in the study area contain Eutric vertisols only. The farming system has evolved in response to both internal and external forces, and this evolution can be divided into three periods:

1) The period before the area was incorporated into Meniliks empire (before 1898), when livestock production dominated the farming system (Lexander, 1968).

2) From 1898 to 1960s, when Indigenous farmers experimented with crop production methods introduced by migrants from shoa. During this period farming, practices were characterized by different rotational systems that included long follows from 1996 to the present small grain cereals have continued to dominate the farming system. Wheat area and yield have increased substantially, but farm sizes have diminished greatly because of population pressure, to the extent that some farmers can be considered uneconomic (CADU 1973; Zena, 1976).

In general, farmers have shifted out of a livestock-dominated system to crop-livestock systems. The major crops in the area are now wheat, faba bean, barley, sorghum and teff. However, barley is the most dominant in the higher altitude of the zone, whereas the major crop in the middle altitude areas (chilot yirga et al., 1989). Besides being a subsistence crop, wheat is also a major source of cash for farmers.

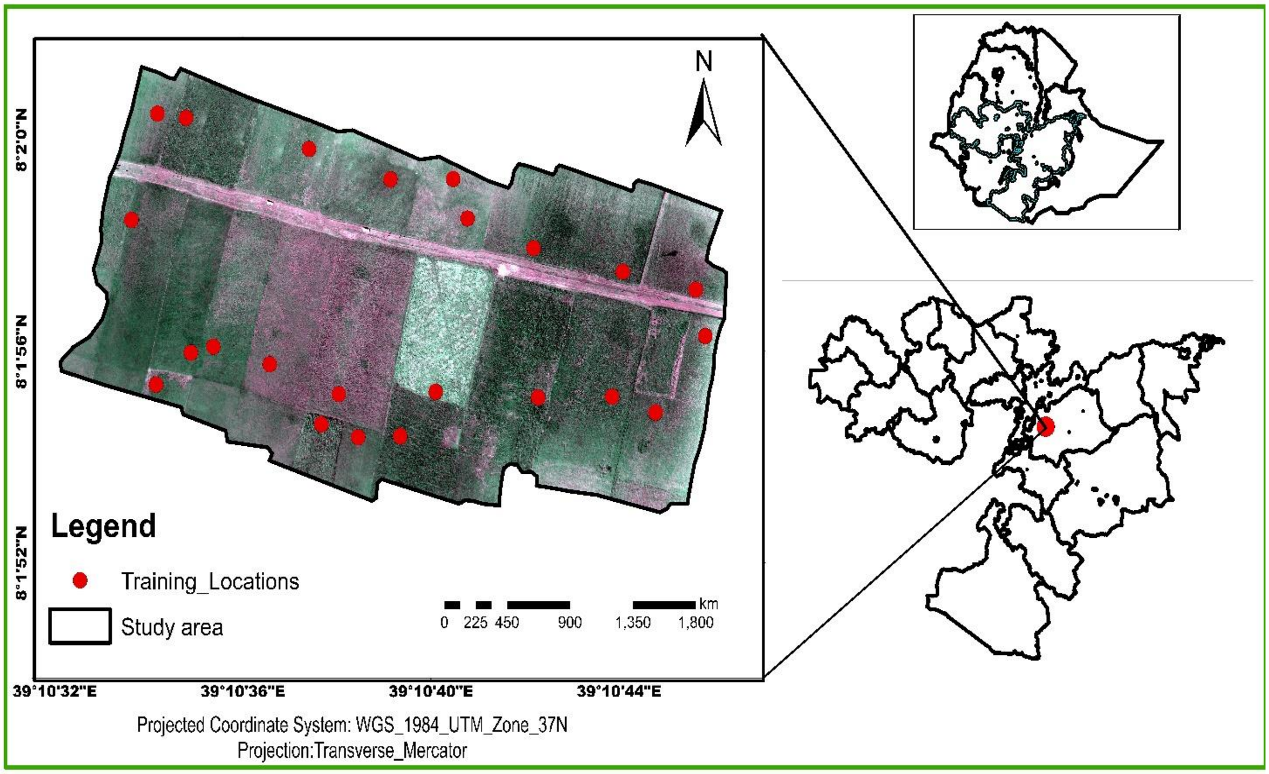


Figure 3.1. Study area map

3.1.2 Materials

3.1.2 .1 Instrument description and application

3.1.2 .1 .1 Parrot blue grass - Drone

Emerging drone technology have the great potential to develop how to monitoring crops. The rapid development technology in advances in recent years have dramatically increased affordability and ease use of unmanned Aerial Vehicle (UAV) and associated sensors. The multispectral sensors, parrot sequoia capture spectrally accurate high-resolution (fine grain) imagery in visible and near infrared part of electromagnetic spectrum, providing supplement to satellite and aircraft image.

Parrot blue grass is equipped with multispectral sensor, parrot sequoia. This small, light, multispectral camera four spectral bands in visible light and non-visible infrared light to analyze the health status or monitoring the crop status and crop type mapping. Sequoia has 16mp RGB camera and internal memory of capacity of 64GB. The screen of these instruments indicates about orientation of the multispectral sensor and the sunshine sensor, Irradiance screen also show the light intensity of each band (Green, Red. Red Edge and near infrared). The parrot sequoia collects data of features in four spectral band, displayed table below.

Table 3. Available Bands and with their wavelength from the parrot sequoia

Band	parrot sequoia (nm)
Green	550
Red	660
Red edge	735
Near infrared	790

Calibrating Sequoia – before using sequoia the calibration is needed. The two sensors (multispectral and sunshine sensor) should be properly connected to the drone. It is recommended that calibration of these sensors at the same time, it is possible to calibrate each separately but sunshine sensor must be connected the Multispectral sensor to be calibrated. The multispectral sensor apear purple when a calibration is needed. There are three alternatives when such conditions occur: 1) turn the drone on the Z axis (yaw-green on the scheme) until the multispectral sensor indicator light flashes green 2) turn the drone on the y axis (pitch-red on the scheme) until the multispectral sensor indicator light flashes blue 3) turn the drone on x axis (roll-blue on the scheme) until the multispectral sensor indicator light changes color. The main important in sequoia calibration was once the calibration is complete; the color of the multispectral sensor light varies depending on sequoia's status.

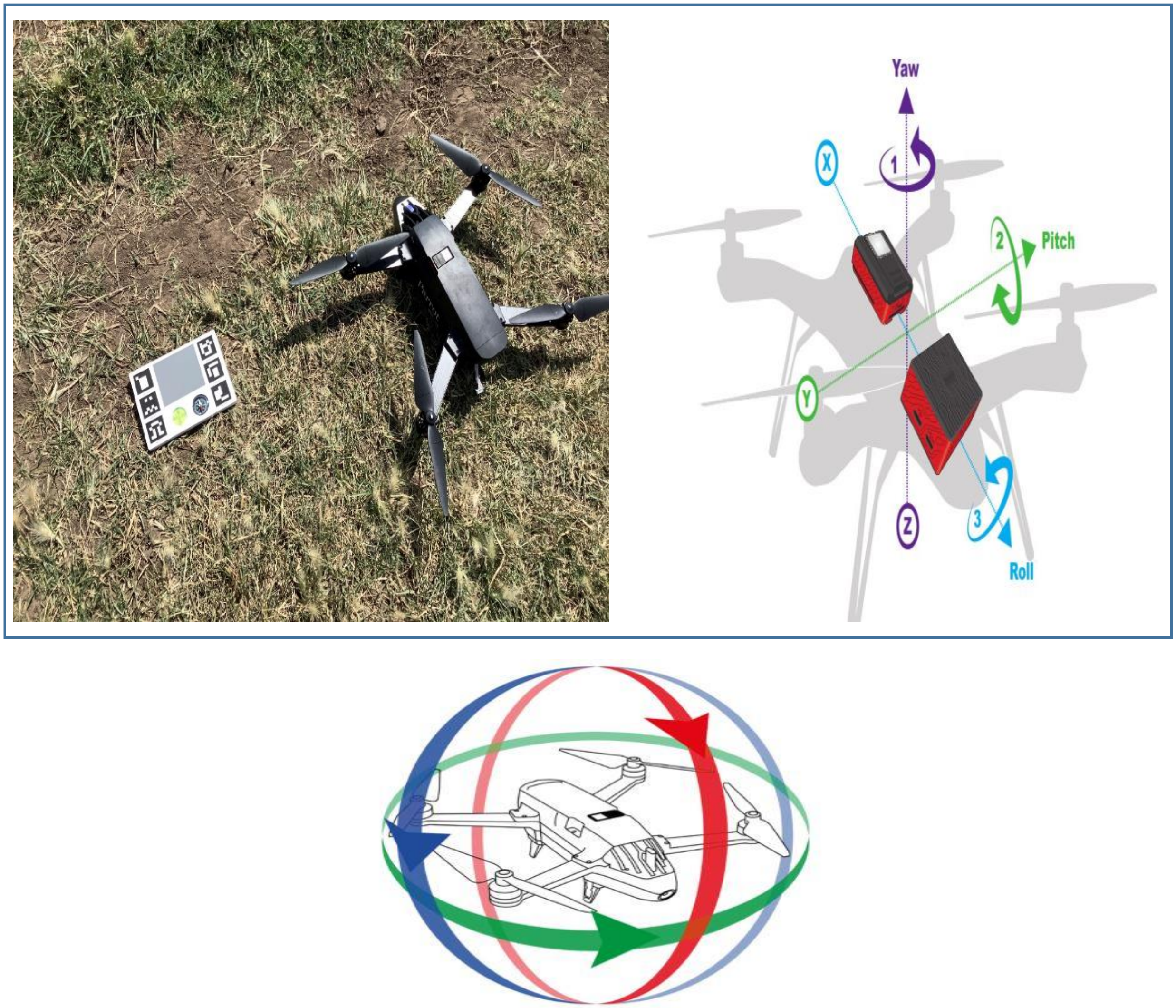


Figure 3.2. Drone calibration panel and Multispectral sensor with sunshine sensor

Parrot Blue grass is specifically designed for agricultural purpose, crop mapping and analysis that may quickly offer actionable information to farmers, researchers, ensures and anyone else who works directly at intervals the agriculture. In recent years, there has been robust activity within the questionable exactness agriculture, especially in the management perspective not only enhance productivity however additionally crop type mapping at farmland.

At massive scale, precise monitoring of cultivated field could be quite challenge task in order that this technology (Drone) is applied to map crop type in the cluster of farmlands, with drones equipped with multispectral camera and comparison within satellite product, which is sentinel 2A at the same study area. The procedure to conduct Drone flight and capture data for precise information of crop type needs Flight planning, site selection, checklist before takeoff and data transfer at each flight during fieldwork at the site. For example, checklist before takeoff has eight requirements.

<u>The day before the flight</u>

Check weather conditions:

- Do not use if it is raining or snowing
- Do not use if there is a fog
- Do not use if there is a wind speed at 3m/s or 30km/hr

Make sure you have all the necessary authorization from the local authorities

Charge the drone batteries, smartphone and or tablets

Prepare flight plan

<u>The day on the field</u>

1. Make sure you 10m have diameter of free space for takeoff and landing
2. Check the flight area has no obstacles
3. Make sure parrot blue grass has detected GPS signals in the free flight pro or pix4D capture
4. Check that the propellers of parrot blue grass has been correctly fitted and tight
5. Check that the battery on drone is fully charged
6. Check that the selected distance is sufficient for your flight
7. Make sure parrot sequoia lenses and the front camera of the Drone are clear
8. Free up enough memory on the SD card or internal memory of multispectral sensor to recover all pictures taken during the flight
9. Make sure that the two sensors (multispectral sensors and sunshine sensors) are calibrated

Finally, free flight pro and pix4Dcapture have been installed on the pad, video with image and crop type mapping of the cluster available and captured respectively.

3.1.3 Data acquisition and image processing

3.1.3.1 UAV Data acquisition

Now a day's parrot blue grass is most popular that it makes easier than ever before for experts like agronomists, farmers and researchers to map agricultural farmlands of diversified crops, to scout crops from the air. Parrot blue grass is integrated within different soft wares like free flight pro, pix4Dcapture and pix4Dfield for mapping crop field and needed for further analysis.

Diversified crop types like teff, Faba bean, wheat, barley and sorghum have been captured in the cluster farmland of the study area as shown in (figure 3.3)

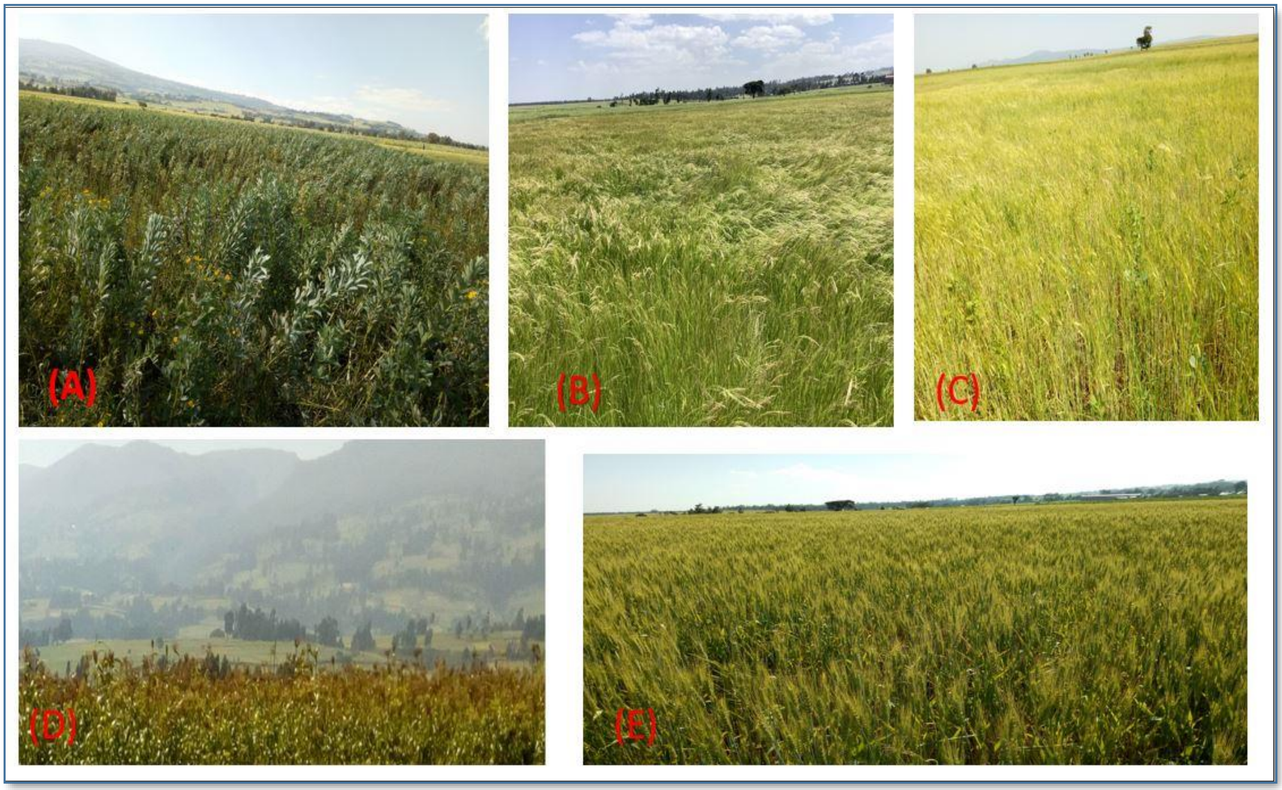


Figure 3.3. Crop types in cluster farmlands :(A)-Faba bean, (B)-Teff, (C)-Barley, (D)-Sorghum and (E) wheat

In this study, 1862 separate images acquired, at an altitude flight of 40m within four-flight mission time to cover an area of the field. Before starting the flight mission, the design of the flight path covering the area of interest was defined, shown in figure 5 and along the altitude of the flight, sensor s and drone configurations of the flight path is typically done using pix4Dcapture –GRID for 2Dmaps.

The flight controlled both manually and automatically in this case study for crop mapping. The approach was applied 80%automatically when capturing images and 20% when landing this is sometimes there have been misleading GPS and misbehave satellites so that intended to use manual approach. In each flight, there have been a setup of calibration that is (12*4=48) calibration images were acquired.at end of the day field survey, different crop images have been collected which are adjacent to each other.   These all images were orthomosaicked thus all these calibrated and images acquired during flight was mosaicked using pix4Dfield desktop (compatible with parrot, which is licensed for a year) and Agisoftware. Both Multispectral image and RGB image have been acquired in October 16/2020 and downloaded via server 192.168.42.2 of the drone in each flight mission in the field.

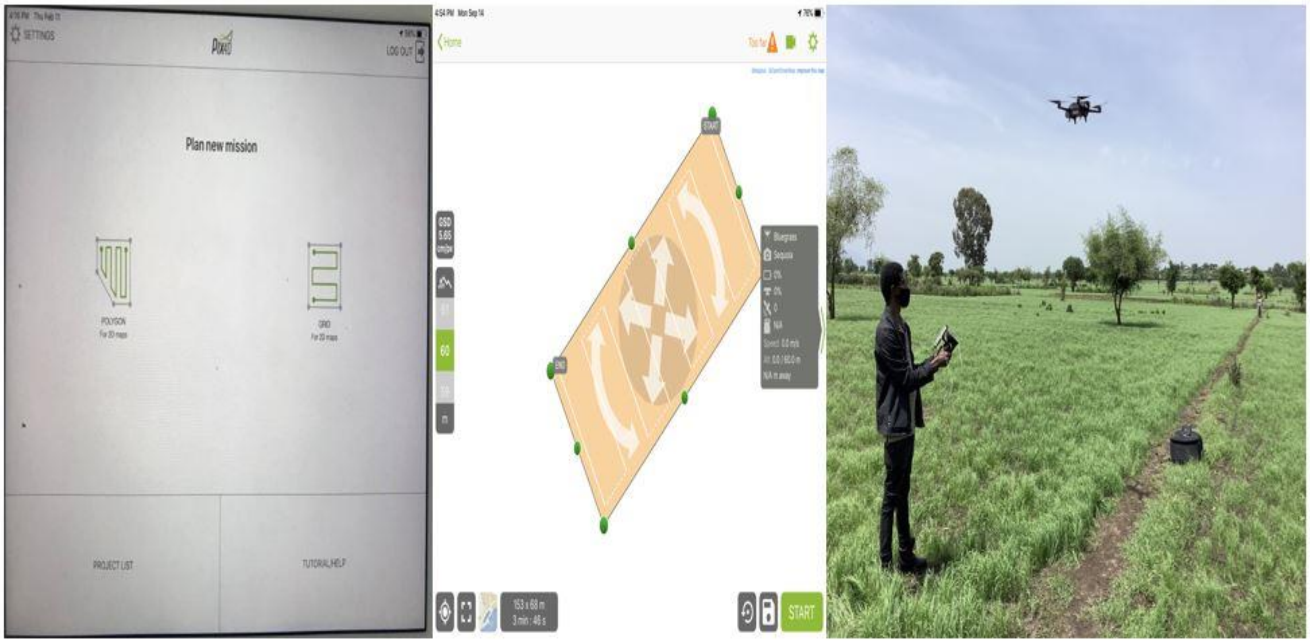


Figure 3.4 Piloting Drone using pix4Dcapture

3.1.3.2 UAV image processing

3.1.3.2.1 Multispectral Drone sensors

Multispectral drone sensors are used to measure the surface reflectance across space for two or more specific bands of wavelengths (e.g., the Red band and Near-infrared band) which is used as a base for calculating vegetation Index like NDVI or to form surface over classifications. Reflectance is the fraction of incident Light reflected from the interface of earth surface.

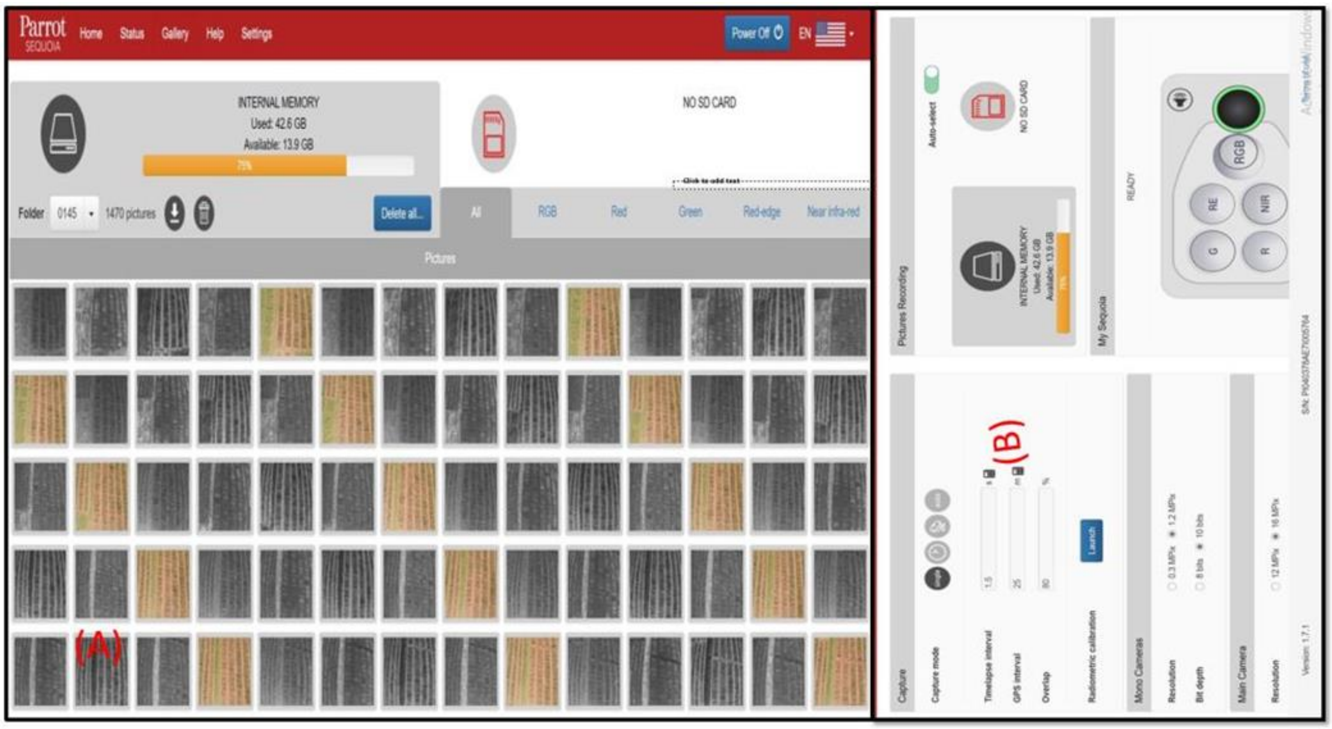


Figure 3.5 (A)-All images of (RGB, Red, Green Red-edge and near infrared) accessibility from drone and (B) the two (SD card or Memory) way options via which one can access the drone data.

Vegetation Index increases the characteristic electromagnetic reflectance signatures of different surfaces, whereas classification often partition images based on these differences. In drone based reflectance feature maps are mostly created by collecting several overlapping images of an area of interest, which are then combined in to a single orthomosaic multispectral image with a software packages such as Pix4Dfiel or agisoft photo scan .Reflectance is not directly measured by multispectral imaging sensors, Instead they measure at sensor radiance, radiant flux received by the detector means that sensor.at detector radiance measurements are stored digital numbers (DN) within the image files for every band at determined bit depth. The DN s provide a proxy of a relative difference of surface reflectance during the ambient light conditions of a particular survey, but if absolute surface reflectance measurements are desired- e. g. for cross site, sensor or time comparison-conversion (calibration)of DN s in to absolute surface reflectance value is significant.

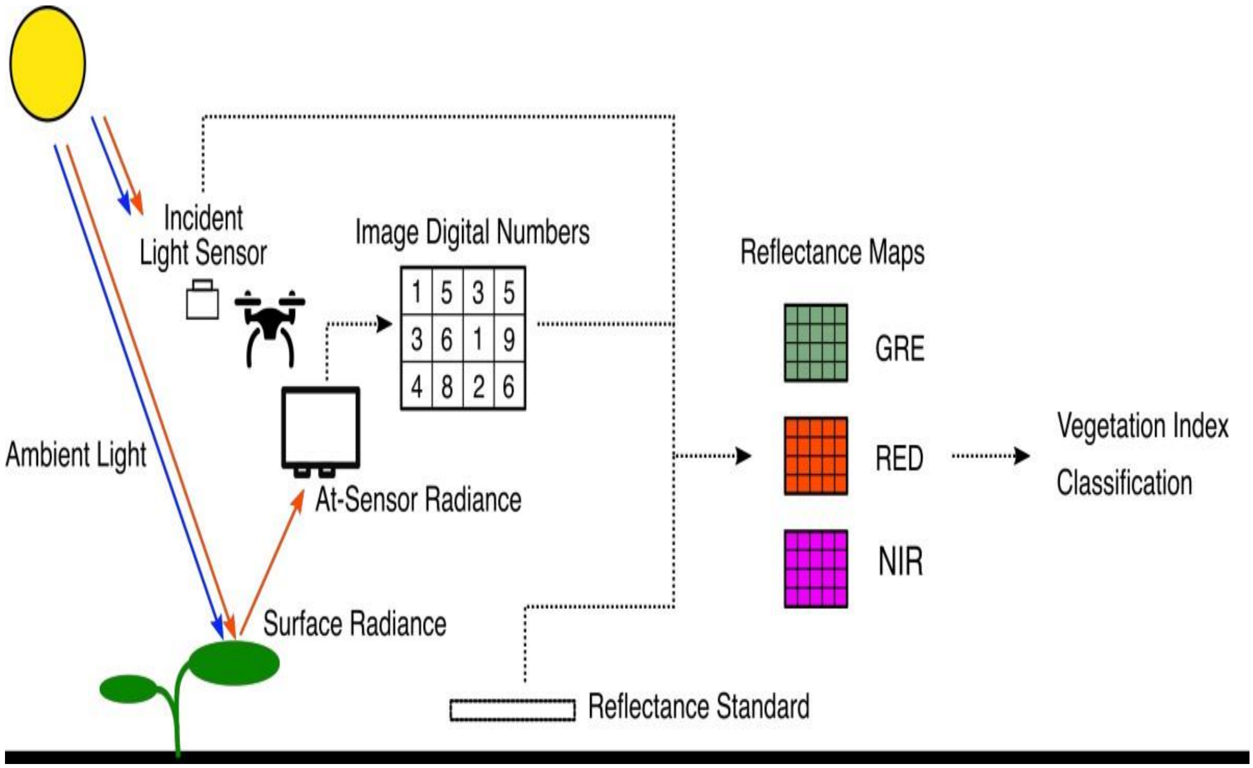


Figure 3.6. Flow of information from surface radiance to reflectance maps using multispectral drone sensors.

3.1.3.2.2 Orthomosaic Generation process

Raw images was acquired using parrot blue grass drone with sequoia camera. Contain geometric distortions while taking image of crop type due to variation in camera orientations and rotation and or turnings. All the images need to be and stitched together to get a single image for further analysis. That orthomosaic have been done using pix4Dfield that it combines all the individuals and overlapped images. Pix4Dfield approach applied to process the drone images and then produce orthomosaic. It is suitable for a set of multiple overlapping images derived from a moving sensor of Parrot blue grass .It allows the structure reconstruction of scene from a number of images with corresponding points, and used to generate orthophoto and 3D surface model from a collection of 2D digital images by calculating the 3D structure of the scene. Another significant in pix4Dfield is feature detection and matching. It is used to extract features in single images that can be matched to their corresponding feature within another image, followed by a rough alignment of images with enough number of features. The points matched together stablish the relative location of a sensor during flight and simultaneously calculate the sensors parameters of each image. even though pix4Dcapture installed on table and or iPad which is used to control and define the flight do have its own GPS and it requires to make it on unless it doesn't connect drone, then capturing images and then it combines each image feature with GPS readings, know what it is and produces the exact locations. The final product of Pix4Dfield is orthomosaic and digital surface model (DSM), GNDVI, NDVI, NDRE can be generated. There are several commercial software's and packages for UAV data processing. Some of these are pix4D mapper, Agisoft photo scan.

Digital Surface model (DSM)

The digital surface model is produced using GNSS positions of the UAV combined with photo matching and the ground control targets and it is the map of elevation of an area on earth. Digital model are scale images wherever within the element values in the pixel values are literally elevation numbers. The pixels are coordinated to world space (longitude and latitude), and every element represents some variable quantity of that space (foot, meter, mile, etc.). The surface model measures the peak of crop growth along the area of study that means the surface value plus crop, rages from 2232.49 to 2244.45 m elevation level.

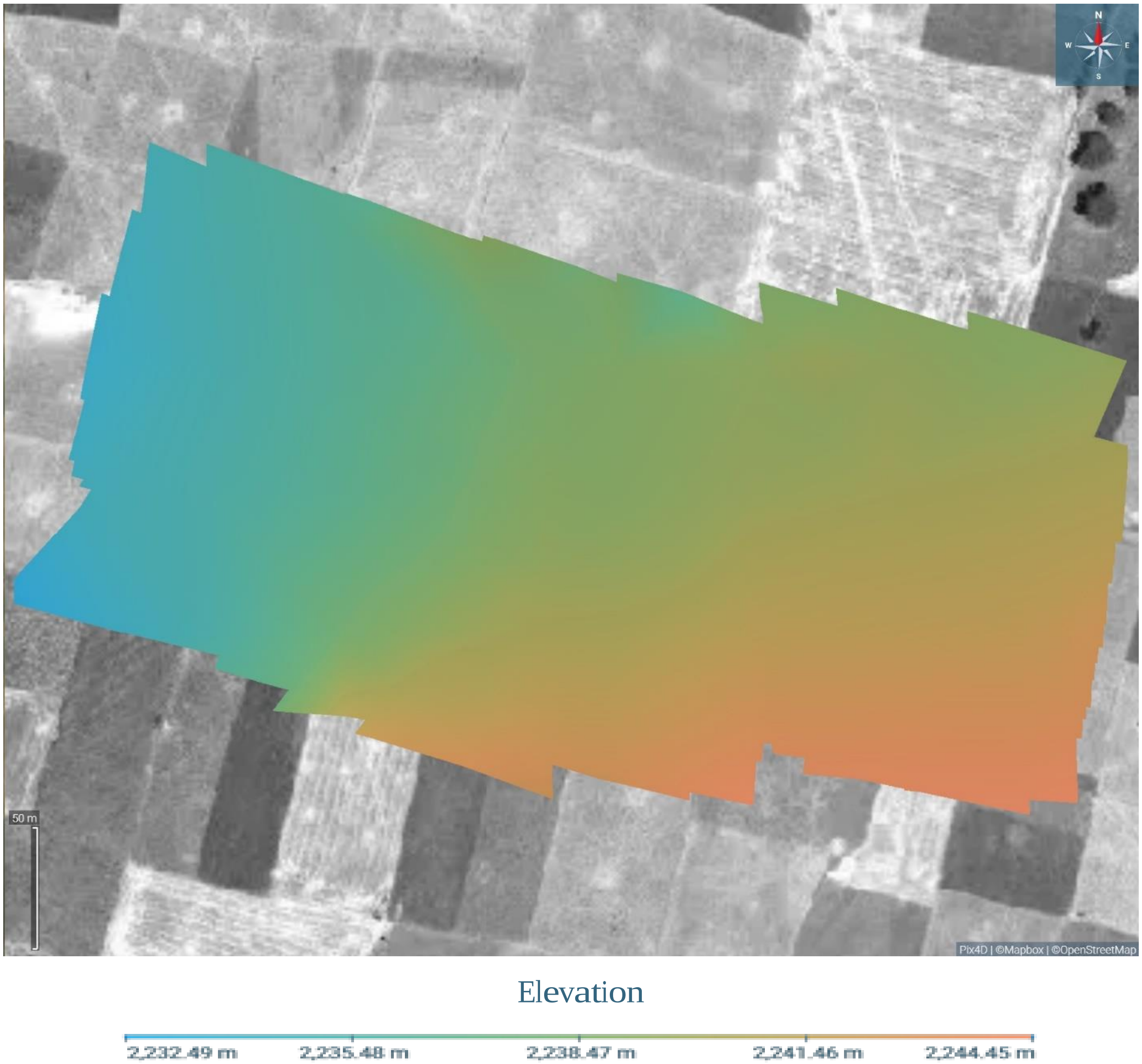


Figure 3.7. Surface model of the area.

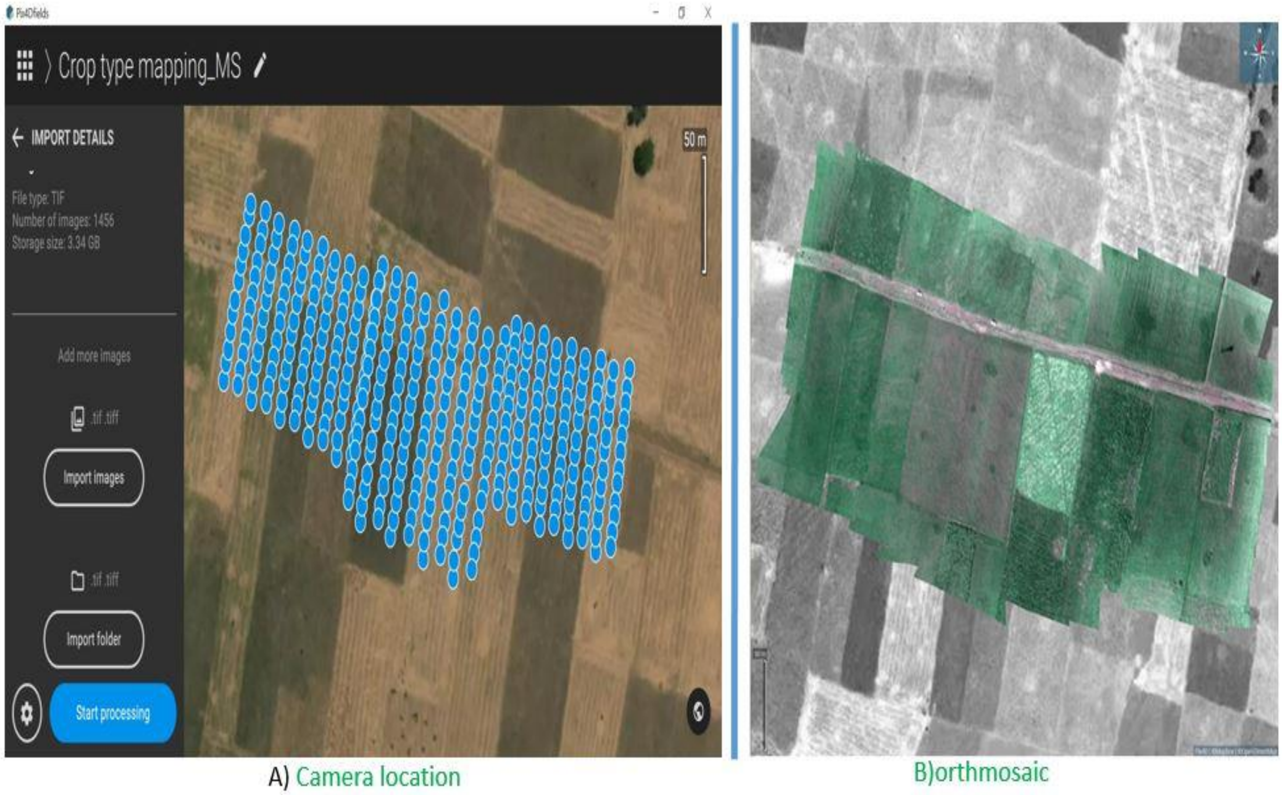


Figure 3.8 Camera locations distribution and orthomosaic image

Dense point cloud –is a collection of 3D points that represent the model. The x. y, z position and the color information are stored for each point of the densified point cloud. It is computed based on the automatic Tie points (ATPs) of processing and it provides a very accurate background for distance, surface and volume measurements. Key point is a large number of point features image taken that are seen well and colorful in the camera visibility while Tie is small in number than key points that it combines those collected in key points that have similar characteristics among them.

DSM- Digital surface model (DSM) is a 2.5 model of the mapped area (.xyz, .las, .laz) .each pixel of the raster Geo-TIFF file and each point of the point cloud contain (x, y, z)information. They do not contain color information for each (x, y) position, the DSM has the altitude of the highest point for this x, y position. This is why it considered being 2.5D model.

DTM-The digital terrain model (DTM) is also 2.5D model of the mapped area after filtering out objects, like buildings crop type trees. It can be exported in Geo-TIFF raster file format. Each pixel of the raster file contains (x, y, and z) information but they do not contain color information.

Reflectance map-is mainly used when the input is multispectral, for each band pix4D produces reflectance map. The main objective is to properly access the reflectance for a particular feature based on the pixel value in the images. The pixel value is influenced by many factors like incoming light, I so, Aperture, shutter speed, sensor speed and optical system. Therefore, pix4D uses the camera positions and the reconstructed model to consider these factors and produce an accurate reflectance map.

Orthomosaic: may be 3D map, for every point contains x, y and color information. The orthomosaic includes a uniform scale and may be used for 2D measurements (distance, surface). It corrects the subsequent issues of the input images. The angle of the camera and very different scale based on the distance that each point of the object ground has from the camera.

Index map-pix4D generates several well-known Indices such as NDVI, as well as custom Indices. Each pixel is associated with an Index map. For each pixel on the map, the value of the pixel is derived from associated reflectance. The following table describes about indices of multispectral and RGB drone imagery.

Table 4. Indices types of Drone image for both multispectral and RGB comparison

Index	Description	Formula	image import type
GNDVI	NDVI index without red channel Availability for areas sensitive chlorophyll	(NIR-GREEN)/NIR+GREEN	multispectral
NDRE	Index sensitive to chlorophyll content in leaves against soil background affects. This index can only be formulate when the red edge band is available	(NIR Rededge)/NIR+Rededge	Multispectral
NDVI	Generic index used for leaf coverage and plant health	(NIR-RED)/(NIR+RED)	Multispectral
TGI	RGB index for chlorophyll sensitivity	GREEN-(0.03*Red)- (0.61*Blue))/normalized to Max value of Red,Green and Blue bands)	RGB
VARI	RGB index for leaf coverage	min(1:max(-1:(Green-Red)/Green+Red-Blue))	RGB

Keys: GNDVI-Green normalized difference vegetation index

NDRE-Normalized difference Red edge

NDVI-Normalized difference vegetation index

TGI-Triangular greenness index

VARI-visibleAtmosphericallyResistantindex

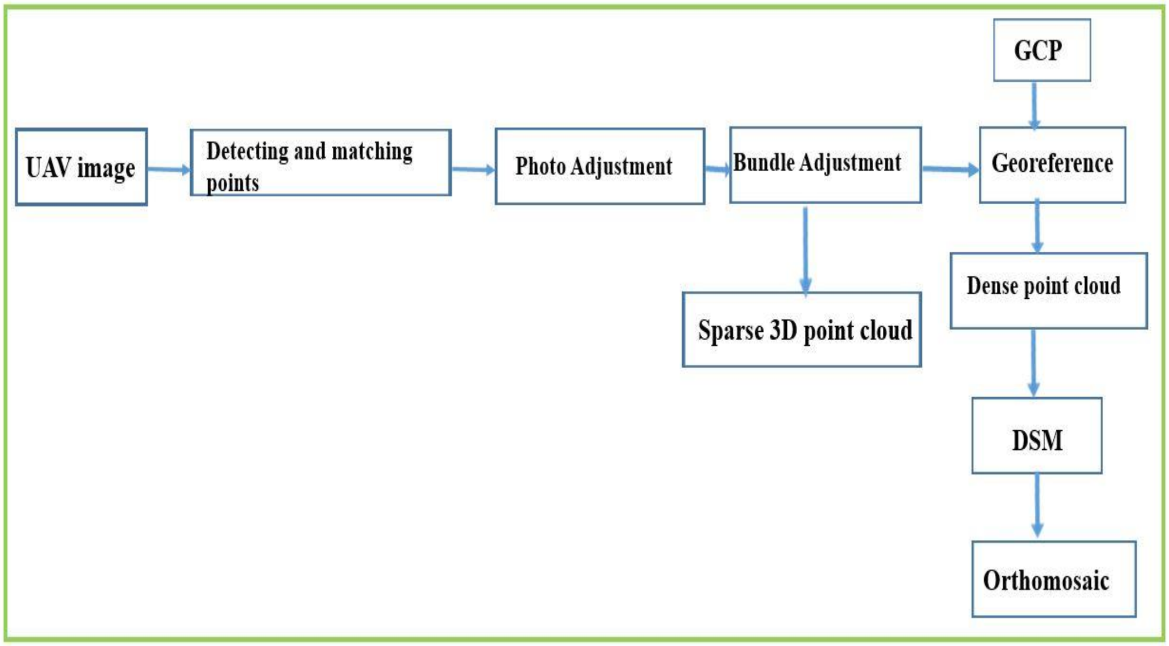


Figure 3.9. The workflow of orthomosaic.

3.1.4 Sentinel 2A MS image

The sentinel 2A MSI image has 13 spectral bands in total, in which four bands (Blue, green, red and near infrared) have spatial resolution of 10m and 6 bands including (SWIR) have spatial resolution of 20m. With its 13 spectral bands, 290km swath width and high revisit time. Frequency, sentinel 2A MSI supports a wider range of land studies and programs, and reduces the time required to build a European cloud-free image archive. The spectral bands of sentinel 2A will provide data for land cover /change classification, atmospheric correction and cloud /snow separation.

Table 5. The comparison of band wavelengths (nm) of parrot sequoia and sentinel 2A (10m)

Sensor	Blue	Green	Red	Red edge	NIR
Parrot sequoia	-	550	660	735	790
Sentinel 2A (10m)	492.4	559.8	664.6	-	864.7

3.1.4.1 Sentinel 2A acquisition

Sentinel 2A data acquisition and quasi-real time production (local station) will offer regional (within the station coverage) quasi-real-time (10-15min from sensing) data services via sentinel cooperative (local stations), offer no conflicts arise with the systematic space and ground phase operations. ESA can support operations in terms of mission coming up with over the local geographical region of interest and provision of satellite-to-ground interference data. In this, study due to persistent cloudy weather coverage and or conditions, the data of sentinel tried to be seen back and forth to close to the temporal data within parrot blue grass drone image. Then sentinel 2A product examined for cloud free coverage for the study area. Using Drone capturing data under cloud is possible and fine but not for satellite product. Thus, the only free cloud coverage image on 20 October 2020 was downloaded from free of charge (https://glovis.usgs.gov.com).

3.1.5 Methodology

To evaluate the both UAV and Sentinel 2A crop classification performance, a small subset of area of interest (AOI) will be tested and performed. Firstly, a broad image classification consisting of five crop type classes is performed within UAV data acquired and compared to much more area of interest (AOI) of sentinel 2A data classification of the same crop type. For both data products, the same step-by step approach will be used and tested within multispectral cameras. A more UAV focused crop classification will be performed by classifying a field consisting more than one classes of crops. In another words it focuses on classical broad crop type mapping whereas the other cases really take the advantage of UAV high spatial resolution for examining the variation with sentinel 2A defined classes of crop type mapping.Crop classification, orthomosaic of both multispectral and RGB, and accuracy assessment of MS have been done. First, UAV data, sentinel 2A and Training location had already acquired. These all data was preprocessed (camera calibration, photo alignment, dense point cloud generation – this based on the estimated camera positioning of scouting crop types. Then, it is to calculate the depth information for each camera to be combined by Ties and into single dense point cloud, which provides to generate orthomosaic. For crop classification, Random forest (RF)approach, used in machine learning algorithm on R software by exploring different packages of machine learning and also UAV spatial resolution impact on crop classification explored. The general workflow of UAV data and Sentinel -2A for crop classification approach is described in (figure 3.10)

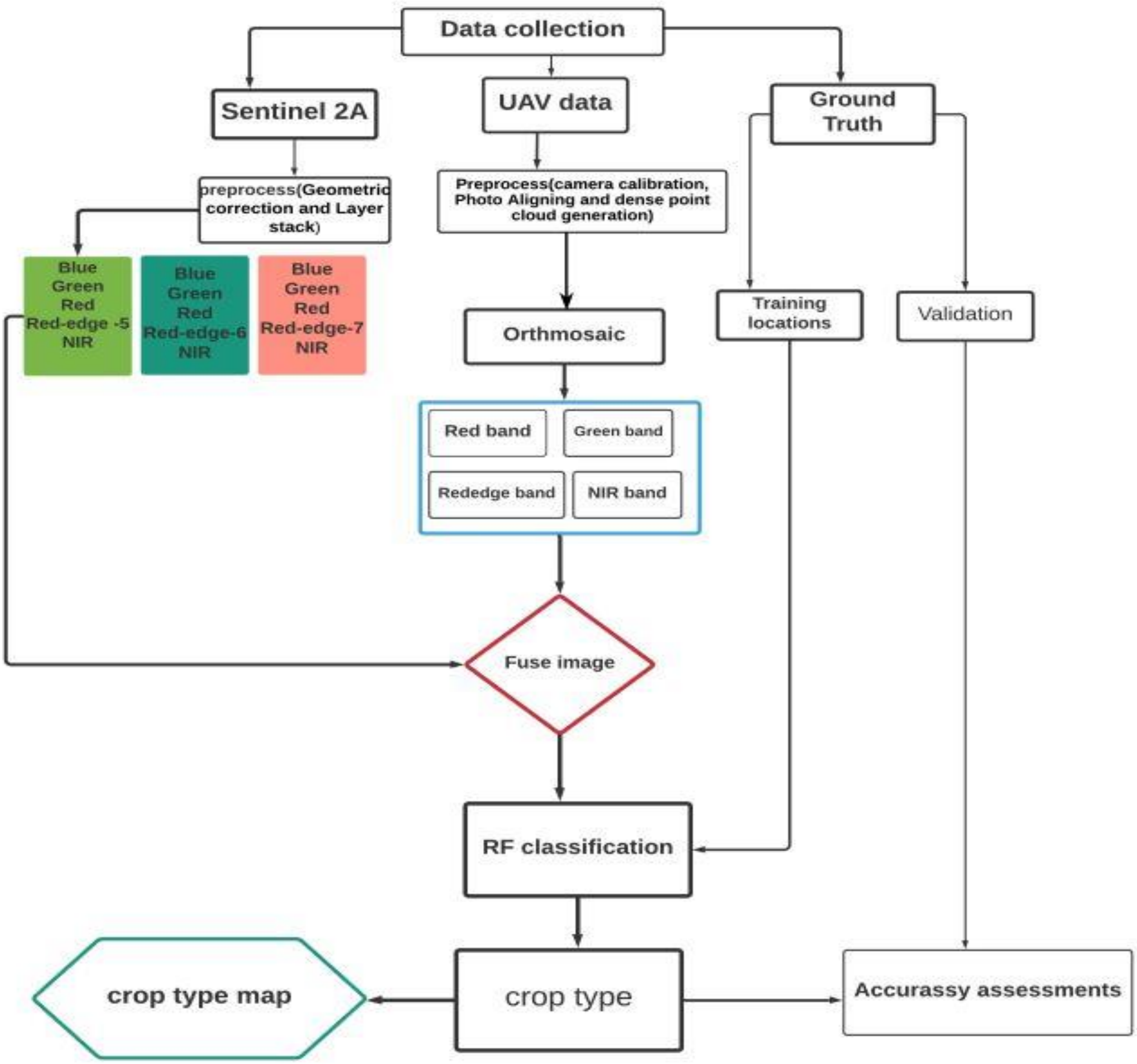


Figure 3.10. The general work flow chart of the Research

3.1.6 Data fusion approach

The Gram Schmidt transformation is a quick, easy and straightforward implement and generates fused images with high integration quality color and spatial detail. The Gram-Schmidt (GS) transformation, introduced by (Laben, 2000). Similar to the principal component transformation it will transform a multidimensional image or matrix by orthogonal transformation to eliminate correlations between the bands of the multispectral information. The spectral and spatial quality of the fused image made with algorithm measure the standard and amount,compared with those of fusion ways like Gram-Schmidt, Fuse go, High-pass filtering, Ehlers, Hyper spherical color space, modified HIS and adaptive wavelet-based algorithms.

In this study, the fusion approach chosen the Gram Schmidt approach, these results show that the criteria-based algorithm is extremely fortunate to keep the color content and offers satisfactory spatial detail enhancement compared to different algorithms.

The process of (GS) transformation follows:

1. The UAV panchromatic band is employed in this study is made by taking the mean value of all bands of UAV images (Yilmaz, 2016).
2. Calculate the mean, standardeviation and variance of UAV panchromatic band.
3. The S2A data are combined into single, simulated lower-resolution panchromatic band. The simulated low-resolution panchromatic band employed as initial band of the low-resolution multispectral information as input of the first multispectral band to (GS) remodel.
4. Calculate the mean and standard deviation of the primary band of the images obtained (GS) transform
5. The UAV panchromatic band (UAV-pan) is then stretched so that it means digital count and standardization match the mean and the standardization of the primary GS band.
6. The stretched high-resolution panchromatic band is then swapped for the first GS band, and the data is reworked back into original multispectral band space producing n+1 high multispectral band. For this Analysis, the S2A (10m resolution) was fused within 3.81m resolution of UAV data set.

3.1.7 Random Forest (RF) Classifier

Random forest (RF) classification involves several steps. Once the appropriate Parrot blue grass data and or sentinel 2A data is acquired, a representative some of pixels from each crop type must be selected and labelled with their respective class, either through ground truth. With training data points, there is a possibility to generate to extract pixel values. At each sample locations, pixel values are extracted from raster data set. These sample pixels are used to train and fit a statistical predictive model that it provides practices various statistical techniques to determine in the training data that it distinguishes between classes, building an algorithm, which can then be applied to predict variables used to train the model.

3.1.8 Field work

During Fieldwork, the data was collected in Oda Dhawata Kebele cluster farmland; from 16 October 2020. Image of the crop type acquired using parrot blue grass flying at an altitude of 40m and Garmin Oregon 650 GPS was used to collect training locations of the cluster cropland. These points are used to training and evaluation data for the random forest classifier. Both RGB and Multispectral image produced and the multispectral one was used for further analysis in the study.

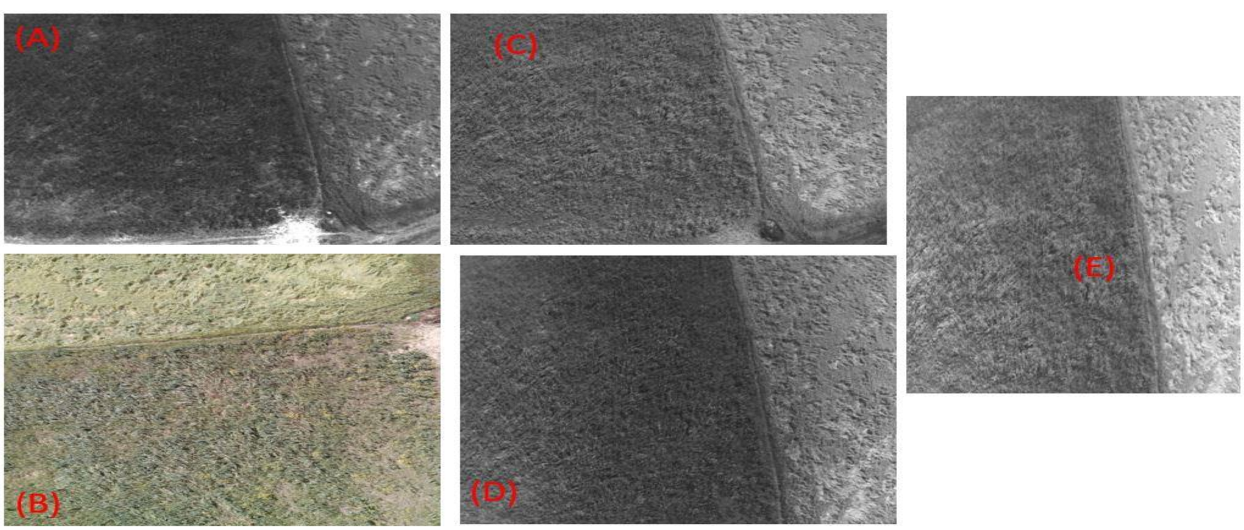


Figure 3.11. Parrot bluegrass product data of both RGB and MS:(A) -Red, (B) -RGB(C) - RedEdge, (D)- Green and (E)NIR.

These training locations have collected for both UAV training and sentinel 2A enhanced area of interest.

Figure 3.12. Training locations and site locations for both UAV and Sentinel 2A

Chapter 4

4. Results

4.1.1 Multispectral Analysis of UAV data

The multispectral image of UAV comprises Green, Red, Red-edge and NIR and the camera model of UAV in which these images captured was called sequoia. The average ground sampling distance (GSD) in between images was 4.19cm and a total area covered was 7.55ha. During stitching the images in orthomosaic process, the average of 10000 key points per image was generated and out of data set of 1456, 100% images calibrated and then all images enabled for further analysis.

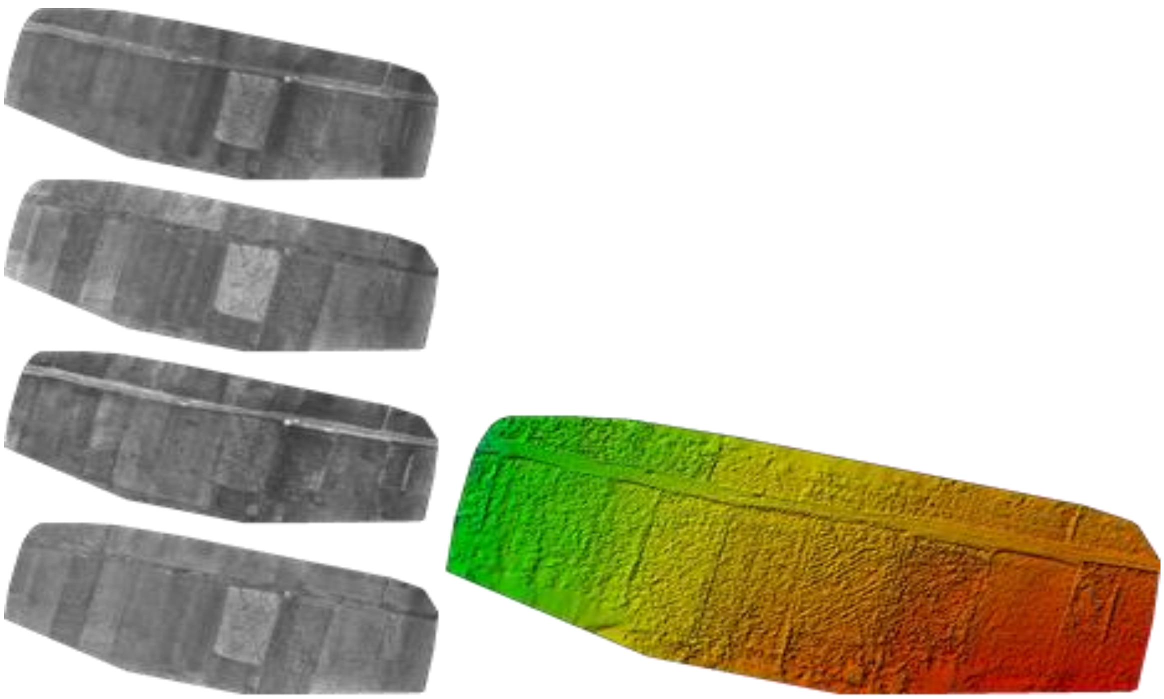


Figure 4.1. Orthomosaic and the corresponding sparse Digital Surface Model (DSM) before densification.

The raw image positions and computed images (GCP) manual tie point's positions were show in figure below

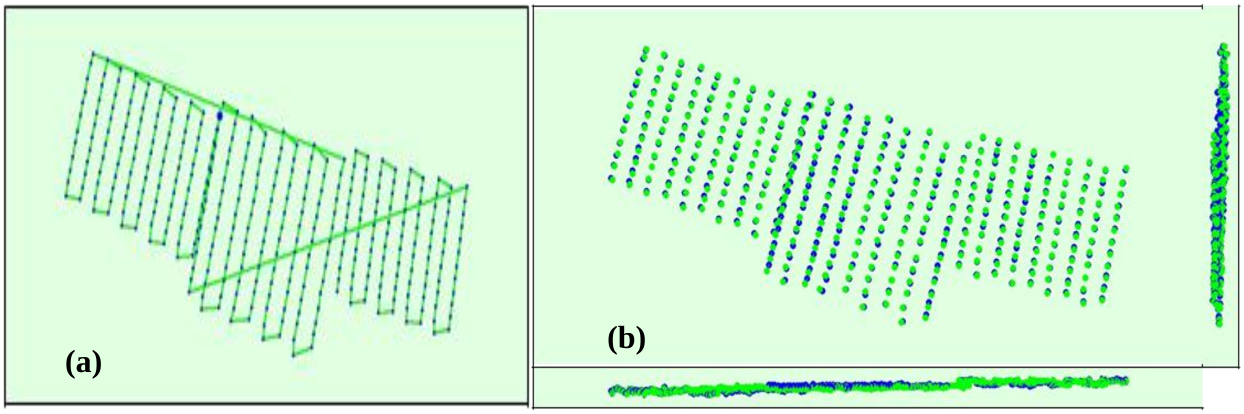


Figure 4.2 (a) Top view of the initial image position. The green line follows the position of the images in time starting from the large blue dot and (b) Offset between initial (blue dots) and computed (green dots) image positions as well as the offset between the GCPs initial positions (blue crosses) and their computed positions (green crosses) in the top-view (XY plane), front-view (XZ plane), and side-view (YZ plane). Dark green ellipses indicate the absolute position uncertainty of the bundle block adjustment result.

Table 6. Absolute camera positions and orientation uncertainties

	X[m]	Y[m]	Z [m]	Omega [degree]	Phi [degree]	Kappa [degree]
Mean	0.088	0.090	0.133	0.125	0.087	0.047
Sigma	0.016	0.017	0.026	0.013	0.018	0.010

In the overlap of the images, the number of images overlapped was computed for each pixel in the study area. it shows that: Red and yellow areas indicate low overlap for which poor results may generated and Green areas indicate an overlap of over 5images for every pixel. Good quality will be generated as long as the number of key point matches is also sufficient for this area (see figure 4.3 (b) for key point matches): the darkness of the links indicates the number of matched 2D points between the images. Bright links indicate weak links and need to manual tie points or additional images. Dark green ellipses indicate the relative camera position uncertainty of the bundle block of adjustment result.

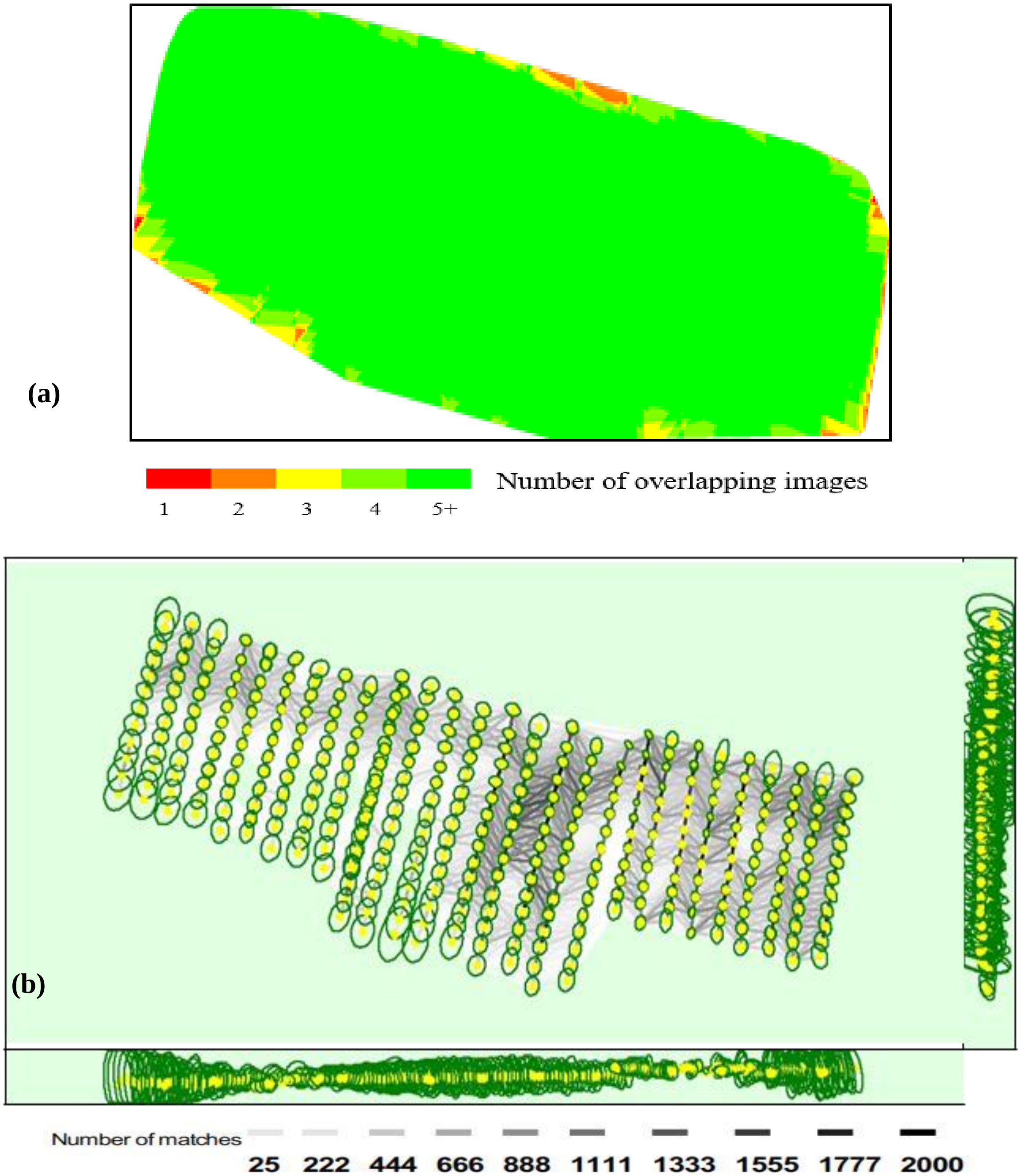


Figure 4.3 (a) number of overlapping images computed for each pixel of the orthomosaic and (b) the computed image positions with links between matched images.

4.1 Image Fusion of UAV and Sentinel 2A using Gram-Schmidt technique

Image fusion is the combination of spectral characteristics of a low-resolution image and spatial feature of higher resolution image to produce the spatially enhanced image. Gram-Schmidt pan sharpening to pan sharpen multispectral data using high spatial resolution data. The source images must be georeferenced to standard map projection, these georeferenced was done during calibration of the UAV in image acquisition process. The pan-sharpening algorithms are used to sharpen multispectral data using high spatial resolution panchromatic data. An underlying assumption of these algorithms can accurately estimate what the panchromatic data would look like using lower spatial resolution multispectral data. The two products of the image data (UAV and Sentinel 2A) are at different spatial resolution .A high spatial resolution panchromatic i.e. the extracted separate bands of UAV can be combined with the multispectral imagery of lower resolution Sentinel 2A.UAV was 3.81m /px at 40m altitude image acquired while sentinel 2A was 10m spatial resolution .UAV and Sentinel 2A was fused together ,During fusion the high spatial resolution represents the information content of the images much more in detail and provides synthetic image close to reality when enhancing the resolution. This provides a radical improvement of the lower resolution of sentinel 2A and the classification of the crop type was done pixel based after fusion. This is very essential and useful to get accurate information of each crop type and well classified. In terms of spectral separability of each crop type, UAV contains four spectral bands that is a little bit challenge to determine and distinguish the higher spectral similarity of crops. Finally, the fused image has a various advantage that it improves the lower resolution to higher resolution of crops, multispectral information and fine scale classification of crop type.

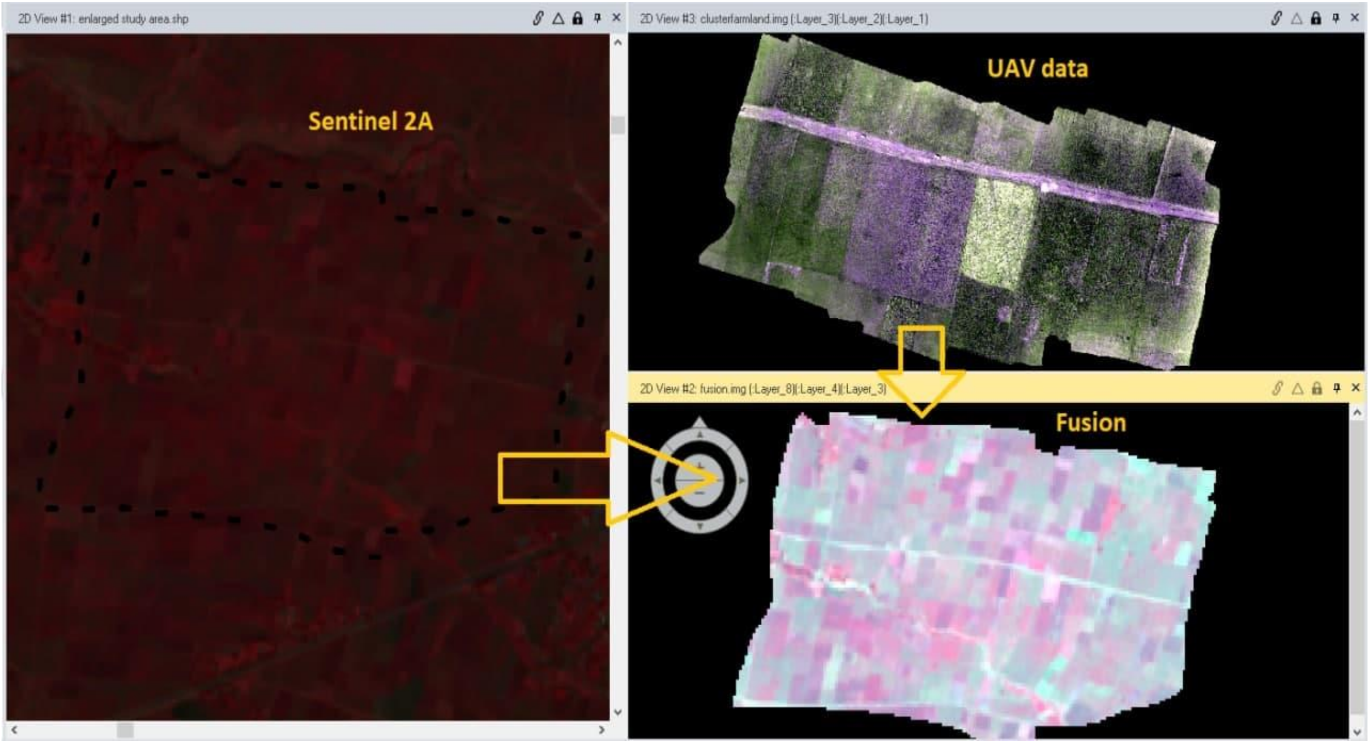
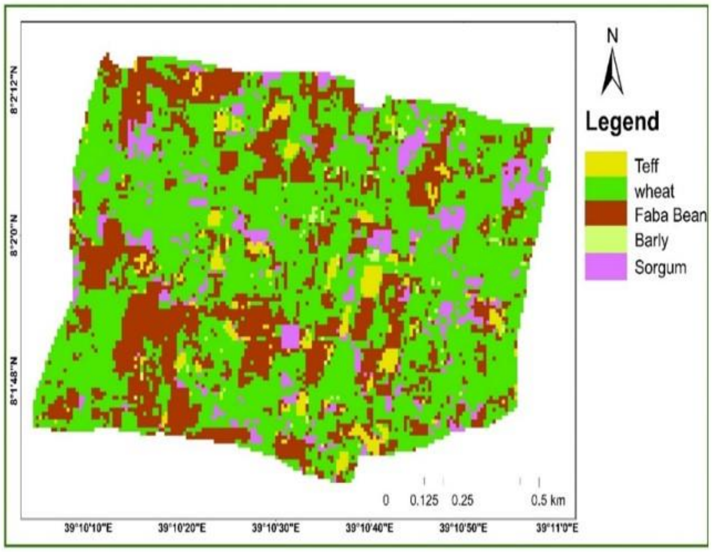


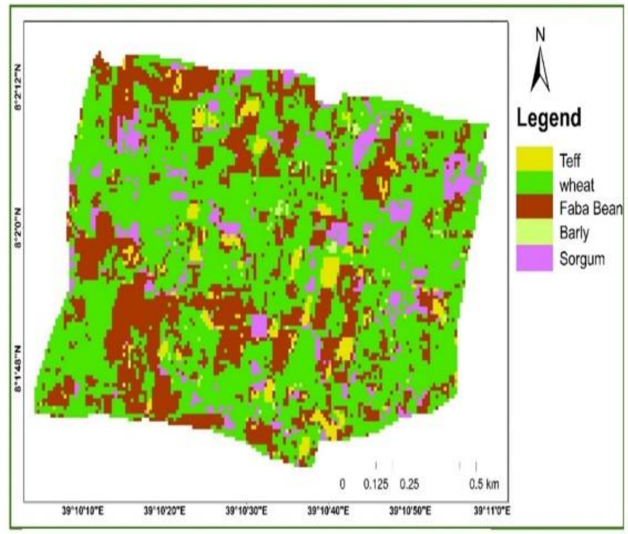
Figure 4.4 Fusion of UAV and Sentinel 2A

4.2 Random Forest classification

After UAV and Sentinel 2A fused together, it gives accurate accuracy assessment this means that the accuracy result was better than using either UAV or Sentinel data of crop classification separately. Therefore, the more fusion data the more accurate result will obtained. The purpose of this fusion was in order to evaluate the performance of sensors in discriminating the crop type in classification of Random forest approach; this is done by splitting the Ground truth data in to two categories: validation and training. So that the cluster farmland classified into five crop types: Teff, wheat, Faba Bean, Barley and Sorghum. The most dominant crop in the farmland was wheat, covering an area of 82ha. In Random forest classification, there are two ground truth data type which is used for training sample and validation. The fused image was feasible in validation of the raw image of Sentinel 2A, both in spectral and spatial resolution of crop types. The crop type map described in figure below.



Fusion classification Using RF



UAV-classification using RF

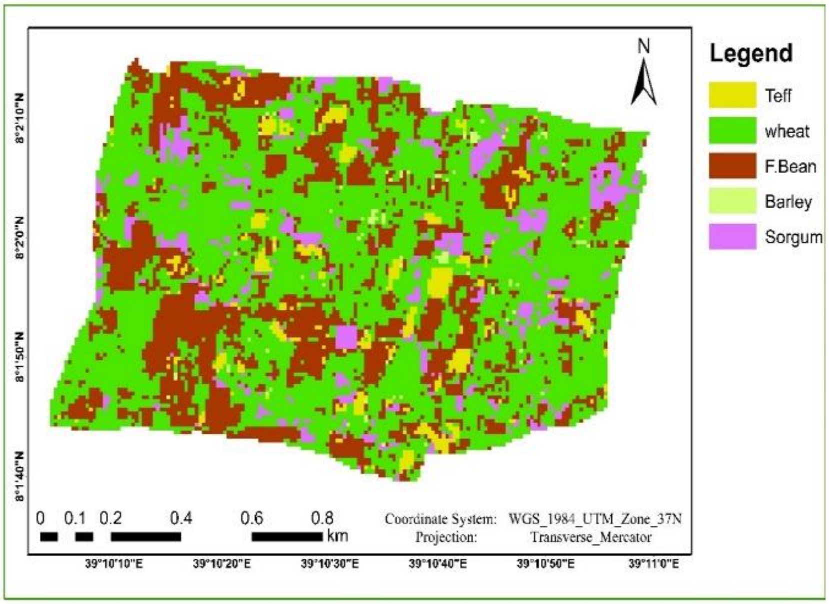
Figure 4.5. Crop type classification map of fused image and UAV using RF

Table 7. Each crop type area coverage and percentage

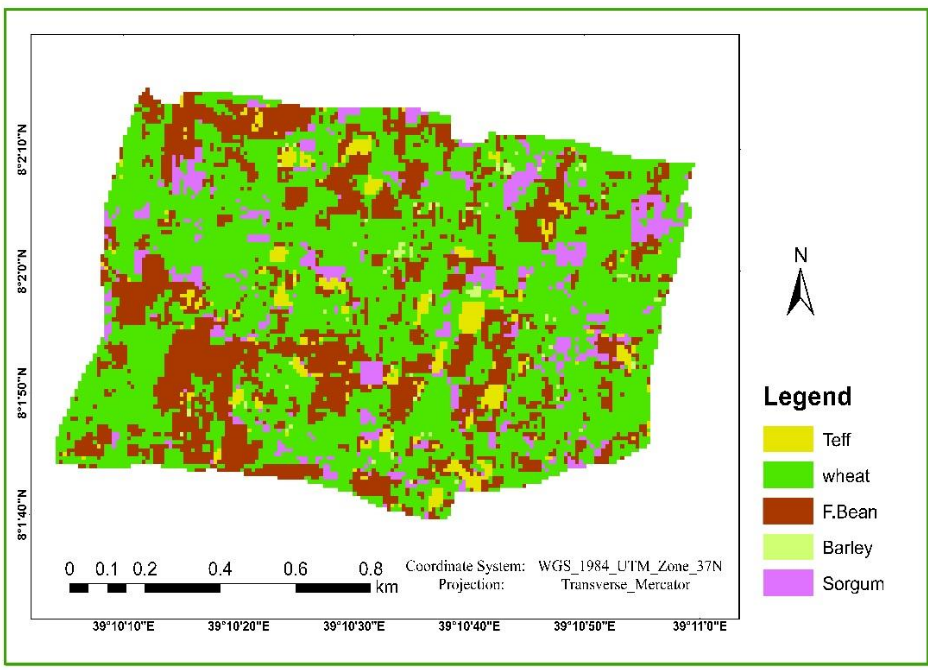
Crop type	Area coverage in hectares	Area coverage in (%)
Teff	6	4
Wheat	82	59
Faba bean	39	28
Barley	1	1
Sorghum	10	7
Totally	138	99

4.3 Maximum Likelihood classification and the sentinel 2A crop type mapping

The maximum likelihood classification method is a tool that it considers both variance and covariance of the class signatures when assigning each cell to one of the classes represented in the signature file with the idea that the distribution of a category sample is traditional, a category may be characterized by the mean vector and also the covariance matrix. Given these two characteristics for every cell value, the statistical probability is computed for every category to see the membership of the cells to the category .Thus, the study conducted to compare the new machine-learning algorithm Random Forest – within the traditional classification method maximum likelihood among each other. Since maximum likelihood has been for a long time, its accuracy assessment resulted 90% and easily implemented



UAV



Sentinel 2A

Figure 4.6 crop type classification mapping in the cluster farmland from UAV data and Sentinel 2A data set.

The most challenge in the classification was, some of the crop type plot was occupied within weeds. This could not be identified in it. However, it was available in between crop types that have been surveyed during field day. It was thought that there is a possibility to detect these weeds in crop classification. Conduct UAV flight at low altitude i.e., less than 10m these gives high resolution but again fragment of the land and obstacles of the flight challenges the task to escape.

4.4 Accuracy Assessments

To validate the classified map of crop types, different accuracy parameters are determined; namely: Overall accuracy (OA), user's accuracy, producer accuracy. All image was classified using RF algorithm and maximum likelihood classification. All points sampled in the field are divided into training data 70% and validation data 30%.since some the classes have different number of points ,a balanced training sample was used where the amount of the points in each class was equal to the number of training points within the frequent class .The overall accuracy assessment RF algorithm resulted 94%, the traditional maximum likelihood classification 90% and UAV resulted 83%.The random forest algorithm-machine learning shows how much fusion plays crucial role in the image classification of crop type. It improves the sentinel data to generate accurate information of crop type in the classification approach. The statistical data of accuracy assessment of the classification of both Random forest approach and Maximum Likelihood classification approach was shown in (Table 8 and 9).

Table 8. Accuracy Assessment table result using Random forest approach classifier for fusion and UAV

Crop types	Teff	Wheat	Faba bean	Barley	Sorgum	Total user
Teff	6	0	0	0	0	6
Wheat	0	5	1	0	0	6
Faba bean	0	0	8	0	0	8
Barley	0	0	0	5	0	5
sorghum	0	0	1	0	4	5
Total producer	6	5	10	5	4	30
Crop types	Teff	Wheat	Faba bean	Barley	Sorgum	Total user
Teff	5	0	0	0	0	5
Wheat	0	12	3	0	0	15
Faba bean	0	0	6	0	0	6
Barley	0	0	0	1	0	1
sorghum	0	0	2	0	1	3

Total producer	5	12	11	1	1	25

Over all accuracy fusion $_{\mathbf{RF}} = \frac{\mathbf{28}}{\mathbf{30}} * \mathbf{100} = \mathbf{94\%}$**, over all accuracy fusion UAV** $_{\mathbf{RF}} = \frac{\mathbf{25}}{\mathbf{30}} * \mathbf{100} = \mathbf{84\%}$

Table 9. Accuracy Assessment table result using Maximum Likelihood classification

Crop type	Teff	Wheat	Faba bean	Barley	Sorgum	Total user
Teff	6	0	0	0	0	6
Wheat	0	5	1	0	0	6
Faba bean	0	0	8	0	0	8
Barley	0	0	0	5	0	5
sorghum	0	0	2	0	3	5
Total producer	6	5	11	5	3	30

Over all Accuracy $_{\mathbf{maximum\ likelihood}} = \frac{\mathbf{27}}{\mathbf{30}} * \mathbf{100} = \mathbf{90\%}$

In this Thesis, the crop type classification was pixel based digital number (DN) values of reflectance curve of each type evaluated. This was done from fused image based of the images. UAV used at a constant flight altitude of 40m, which is high resolution relative to Sentinel 2A. Finally, crop type map produced and found high accuracies in the output of the digital image classification of crop type and the NDVI correlation determined. This indicates how much the fusion image was significant to improve sentinel 2A than the individual classification crop type from sentinel 2A. In general, crop type classification using the results of fusion of UAV and sentinel 2A data enable better crop classification than single data set. The spatial resolution data used of UAV was 3.81m/px while sentinel was 10m. So far, research studies have determined the role of UAV within different satellite data fusion, but no detail research discussion in crop classification and UAV data selection has been conducted. The most advantage of UAV technology is to obtain reliable classification information of heterogeneous crop in fragment land

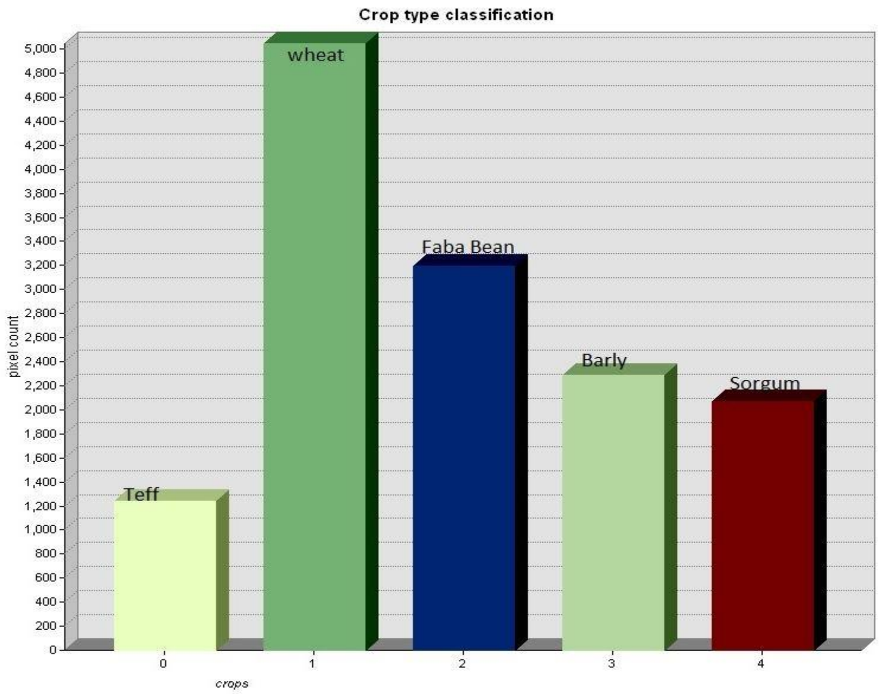


Figure 4.7. Crop type comparison of cluster farmland

4.5 Spectral Reflectance curves of Different crop types

The spectral reflectance curves are created the average value of surface reflectance of spectral bands. This proceeded after UAV and Sentinel images was atmospherically corrected to get true reflectance value of each crop type image. The spectral response of each band is calculated by considering the average response of all pixel values in each crop type in the study area. It has been observed in (figure 4.8). The spectral response of each crops is more distinguishable after band four to last bands range. It is known that NIR(Near-infrared) and or Band4 wave length is useful in vegetation and also in Crop identification soil/crop and land/water contrast.so that the below figure proves this science. Thus, the reflectance of each crop type was increased starting from NIR wavelength.

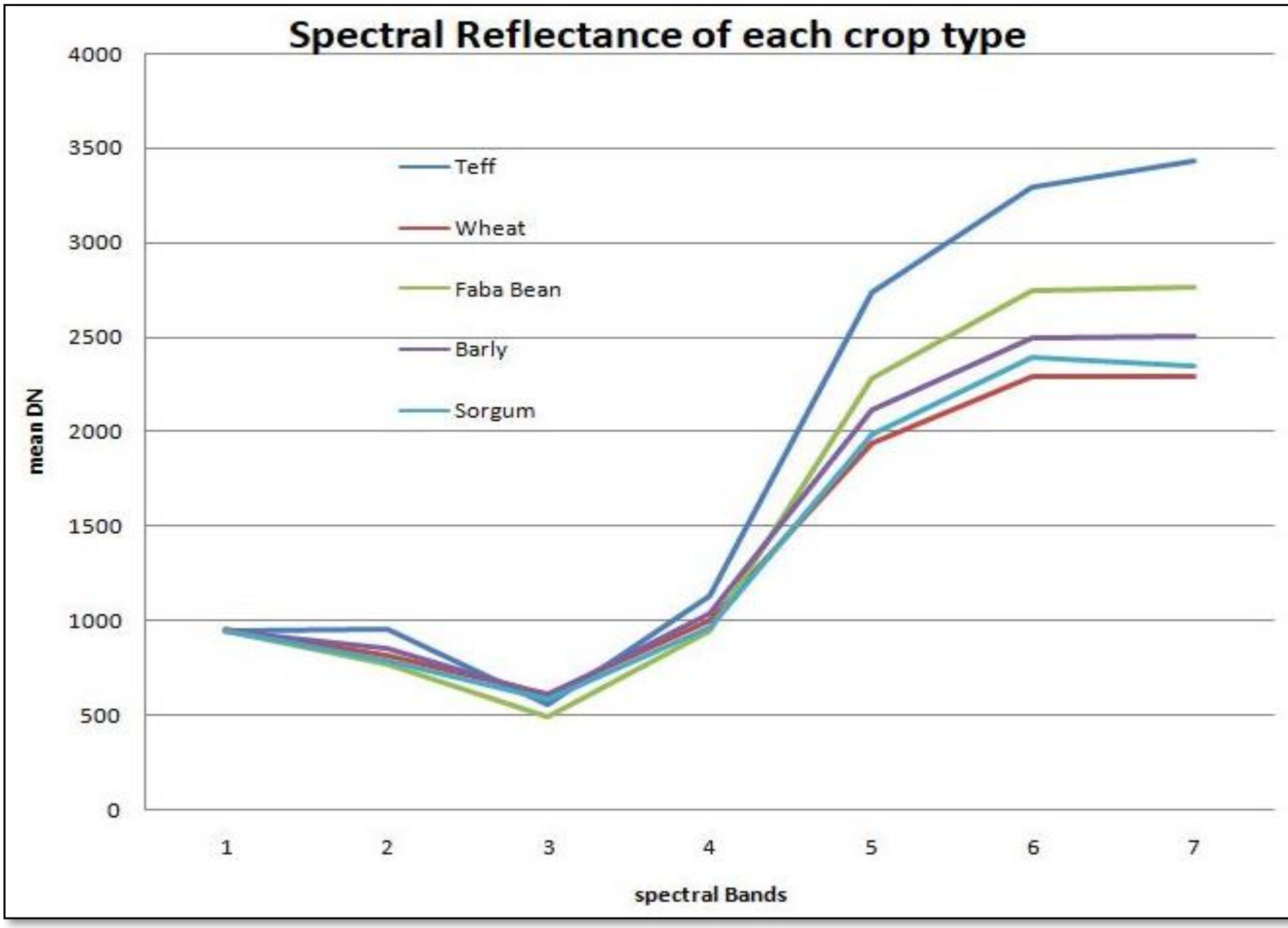


Figure 4.8 Spectral response curve of each crop type.

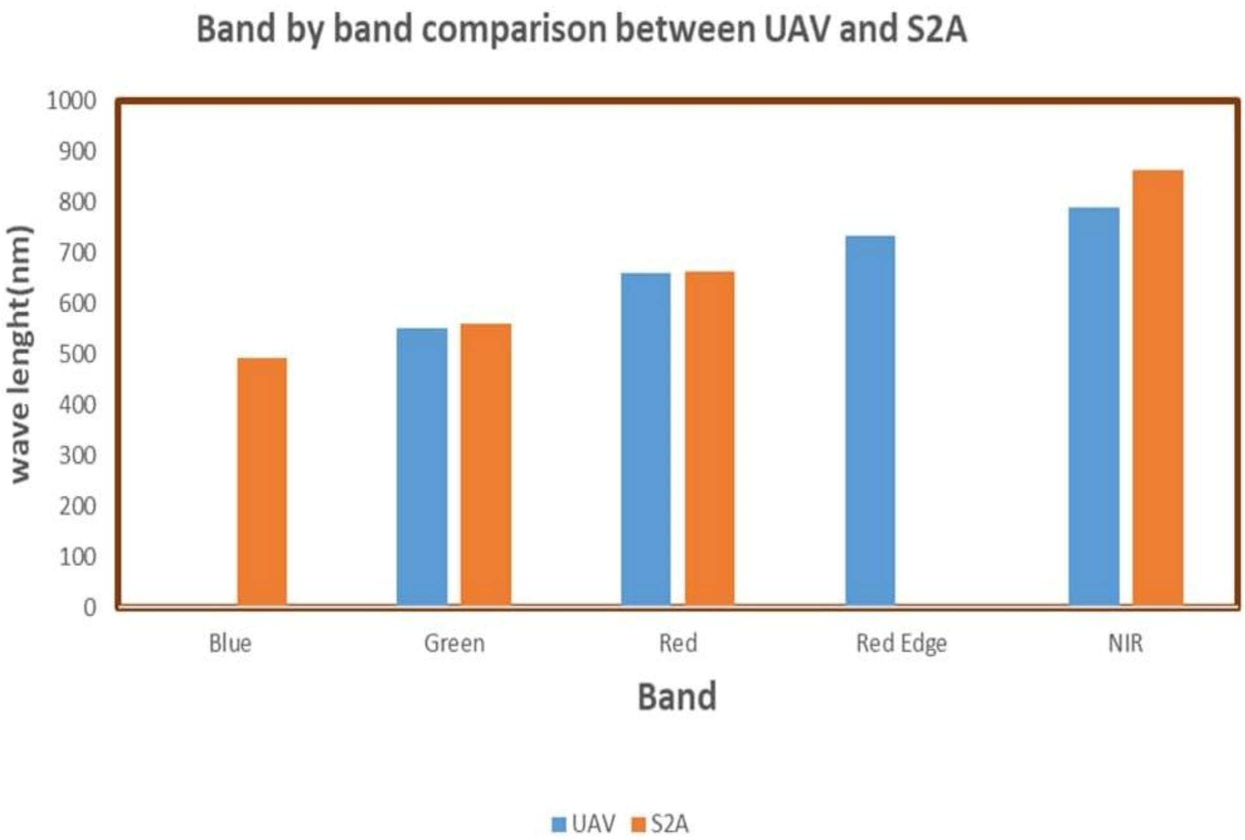


Figure 4.9 Band by band comparison of UAV and S2A

4.6 UAV internal camera parameters and the relations among independency of each bands.

The correlation among camera internal factors determined by the bundle adjustment. White indicates a full correlation between the parameters i.e., any amendment in one can be absolutely compensated by the opposite one. Black indicates that the parameter is very independent, and is not affected by different parameters.

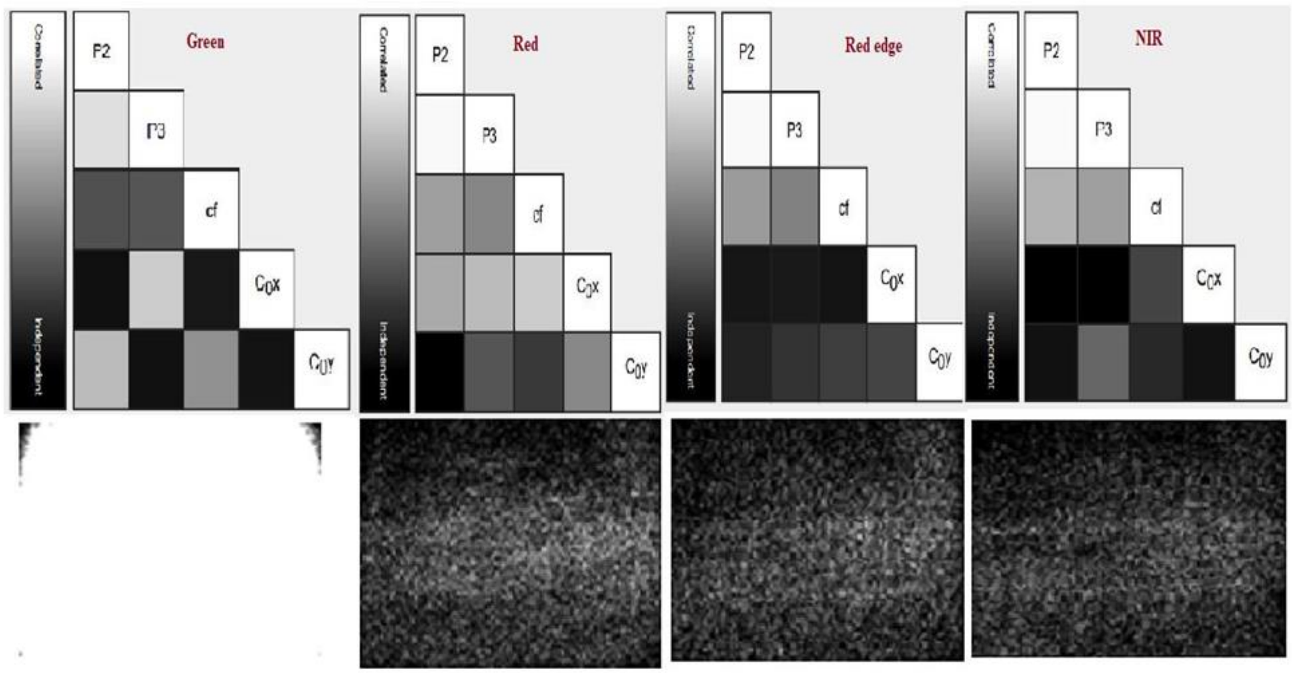


Figure 4.10. UAV internal camera parameters and correlation of color-coded bands.

The Number of Automatic Tie points (ATP_S) per pixel, average over all images of the camera model, is color coded between black and white. The white indicates that, on average more than 16ATPs have been extracted at the pixel location. Black indicates that, on average 0 ATPs have been extracted at the pixel location. The following bands were highly correlated within each other as described in detail in (figure 4.11).

Green –NIR, red-green, red-red edge and Red- NIR was highly correlated value shows 1^{**} and green-red edge and red edge-NIR almost normal correlated value shows 0.99^{*}.

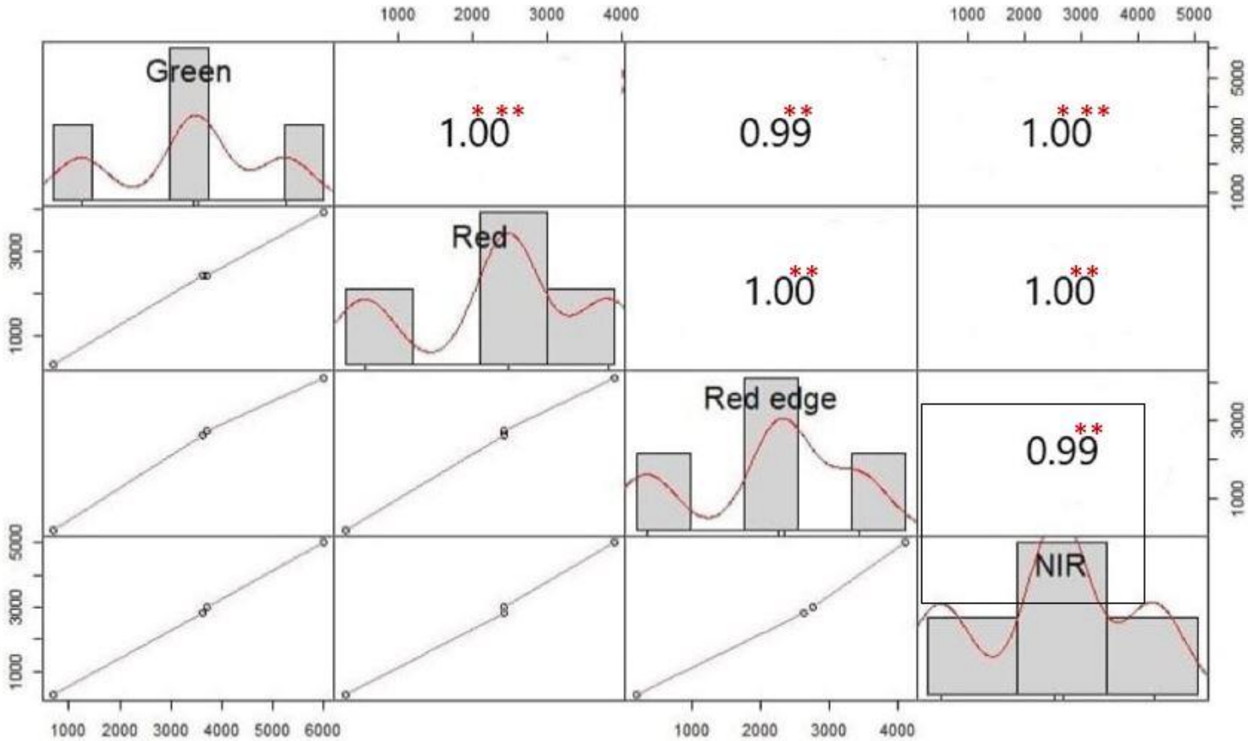


Figure 4.11. The correlation between 2D key points from sequoia camera of parrot blue grass images

4.7 Discriminating of labelled scatter plot distribution of crop type

The analyzed pixel values for the labelled scatter plot distribution categories in the fused imagery contributed mostly the between class differentiation to better understand the feasibility of discriminating of between selected categories of crops and ultimately to interpret the results of the classification model. Although there is a significant overlap in the spectral signatures of Wheat, Sorghum, Faba Bean and Barley. Almost a little bit Teff crop type appears separable. Shown in (figure 4.12)

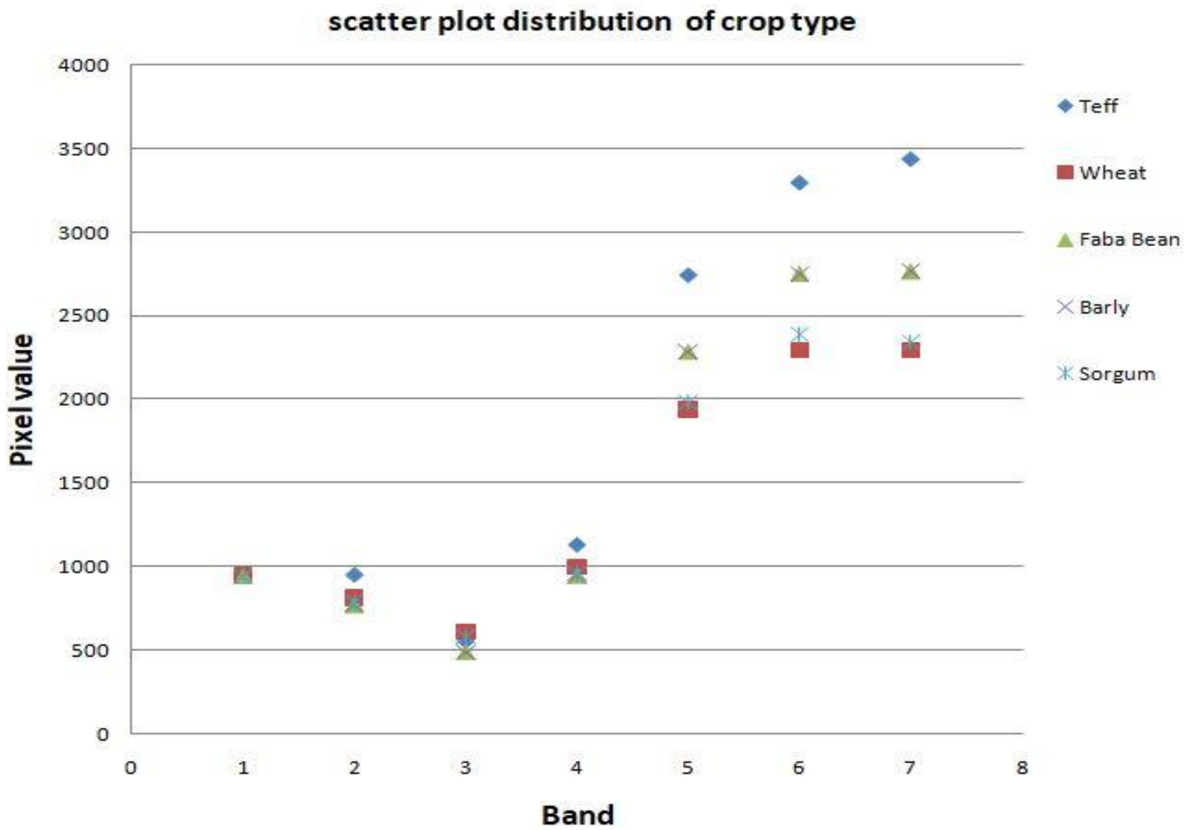


Figure 4.12 the relationship between Bands within crop type

4.8 Spectral Indices of the multispectral image of crop types

4.8.1 Normalized Difference Vegetation Index (NDVI)

4.8.1.1 NDVI comparison between UAV and S2A

The NDVI shows the Vegetated plot in which the highest value is the crop type features that its spectral reflectance was almost good at maturation (finer green) stage while the lowest value indicates the reflectance of each crop type was least, this is due different parameters of farming practices or any other. For NDVI calculation different bands of Sentinel 2A and UAV have used, NIR and Red bands was used in both cases. At the same time the correlation between them were also done (figure 4.13), this was proceeded after multi values to points generated from each NDVI values.

$$\mathbf{NDVI_{UAV}} = \frac{NIR(band4) - Red(band2)}{NIR(band4) + Red(band2)} \qquad \mathbf{NDVI_{S2A}} = \frac{NIR(band8) - Red(band4)}{NIR(band8) + Red(band4)}$$

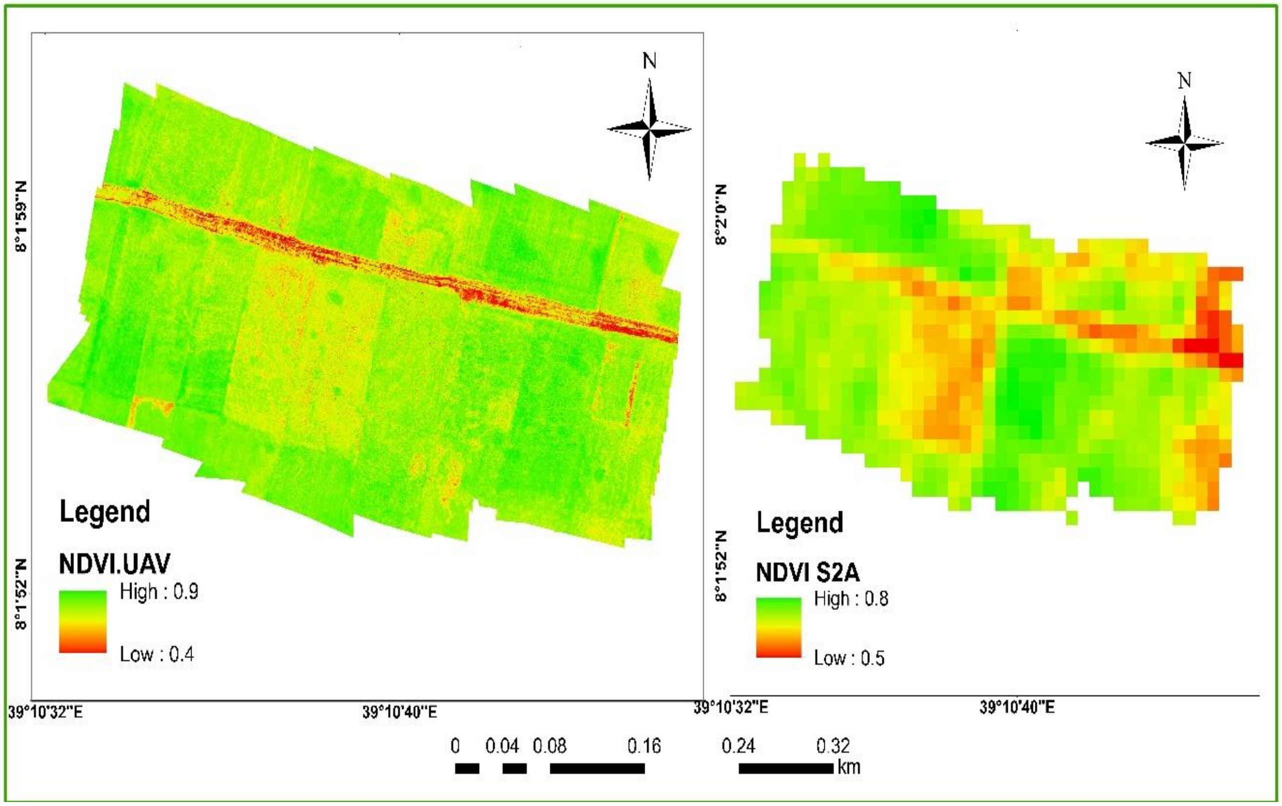


Figure 4. 13 The NDVI map of UAV and S2A

From above NDVI relation in between UAV and sentinel, 2A the high values 0.9 &0.8 and 0.4&0.5 for UAV and S2A indicated how much vegetation reflectance varied from each plot of NDVI. The difference value comes from the spectral reflectance of crop type. This is the time difference acquisition of images from data source. There is a four-day difference acquisition between UAV data and sentinel 2A, that is 16 October 2020 for UAV while 20 October 2020 for sentinel 2A so that the result value of NDVI from each was differ in each crop type spectral reflectance because of the growth crop type. Spectral characteristics of crop depends on crop type in farmland and the health conditions. The NDVI values, examined based on the relationship of crop variation and correlation of UAV NDVI together with available S2A NDVI data. In the study, the four-day difference acquisition data between UAV data and S2A data made a variation value of NDVI calculations, these is due to the different crop growth condition matter.

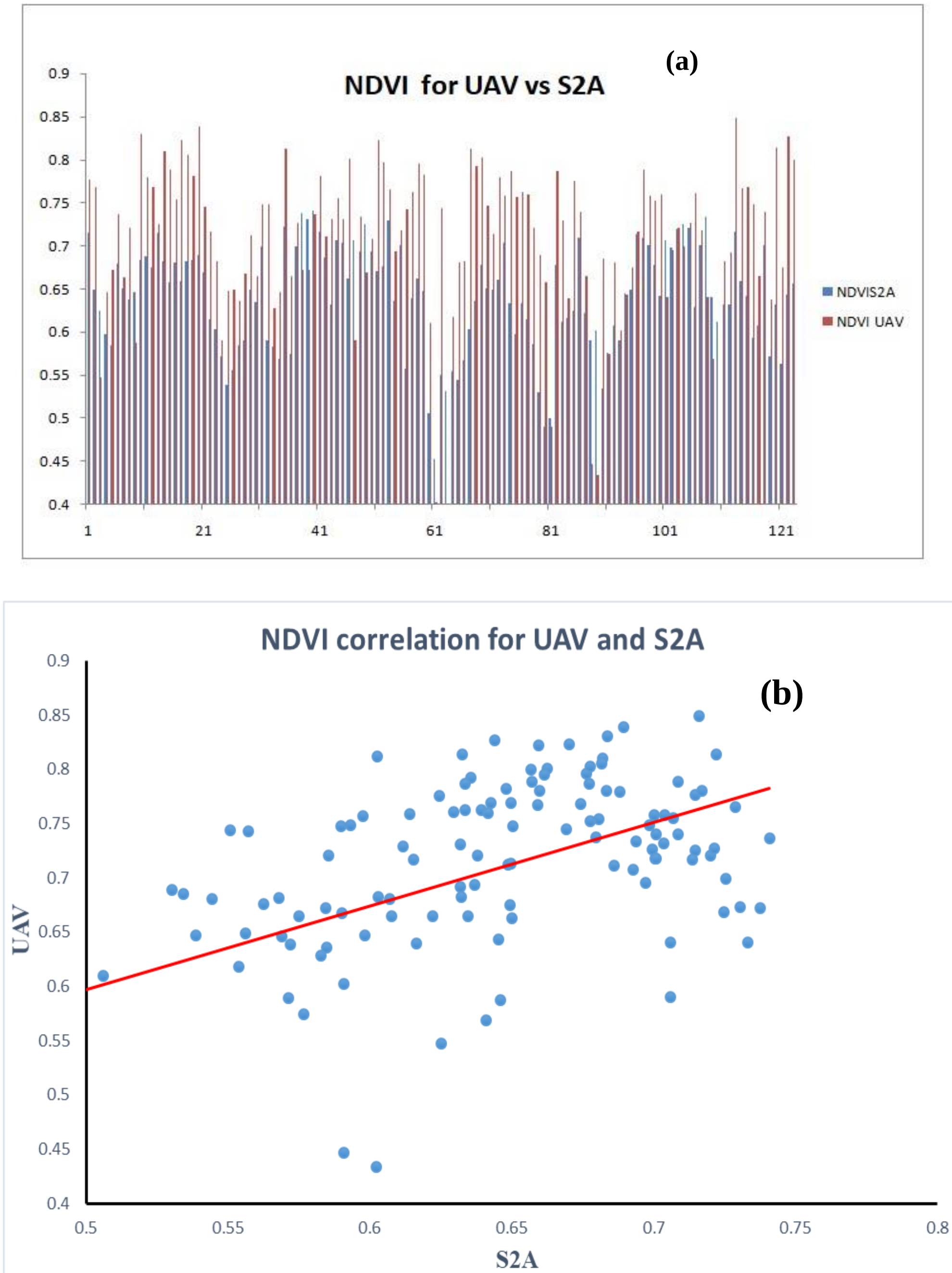


Figure 4.14. (a)The NDVI relation among UAV &S2A and (b) their correlation value of 0.57

4.8.2. Green Normalized Difference Vegetation Index (GNDVI)

It is similar to NDVI except that rather than red spectrum, it measures the green spectrum in the ranges from 0.41 to 0.77 microns and within Ground sampling (GSD) of 3.81m/px. This is an indicator of the photosynthetic activity of the vegetation cover and monitoring plant stress. It is most frequently utilized in assessing the moisture content and nitrogen concentration in plant leaves according to multispectral data, that do not have an extreme red channel, compared to the NDVI index, it is additional sensitive to chlorophyll concentration. It is utilized in assessing depressed and aged vegetation.

$$\boldsymbol{GNVI = \frac{NIR-GREEN}{NIR+GREEN}}$$

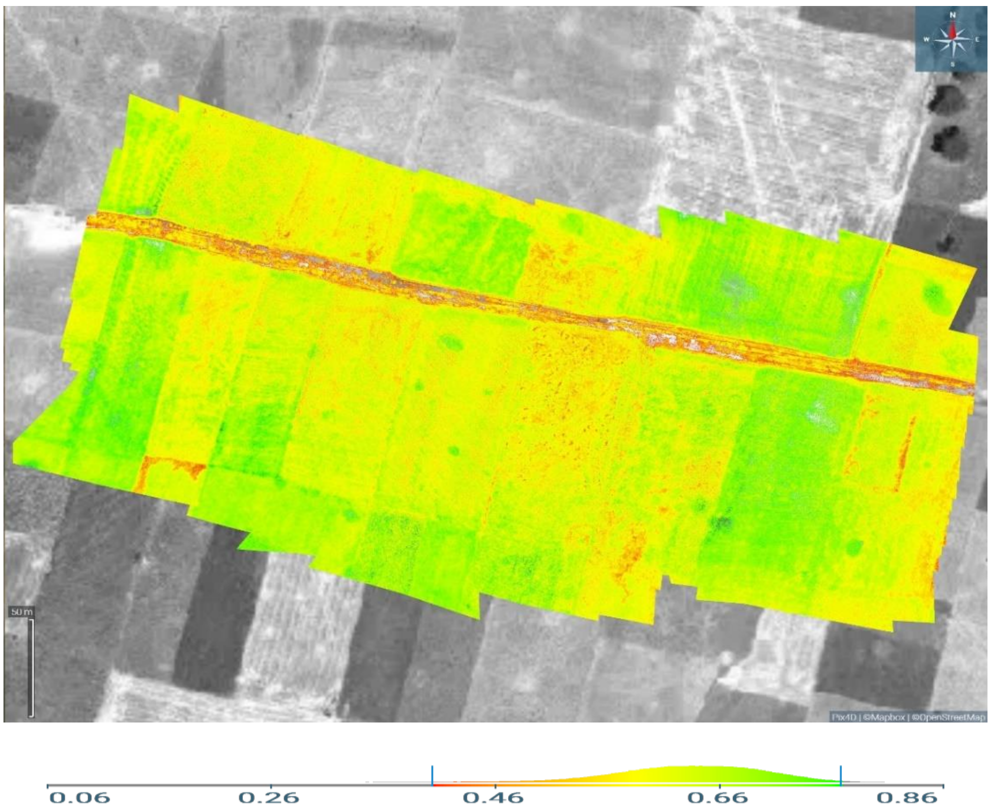


Figure 4.15. Green Normalized Difference Vegetation Index map

4.8.3 Normalized Difference Red Edge Index (NDRE)

Normalized Difference Red edge index is a metric that can be used to analyses whether images obtained from multispectral image sensors contain healthy vegetation or not. NDRE is very sensitive to chlorophyll content in leaves against soil background effect, in this study area, the value ranges from 0.05 to 0.35. It is similar to NDVI but uses the ratio of Near infrared and the red edge as follows: $\boldsymbol{NDRE = \frac{NIR-RE}{NIR+RE}}$

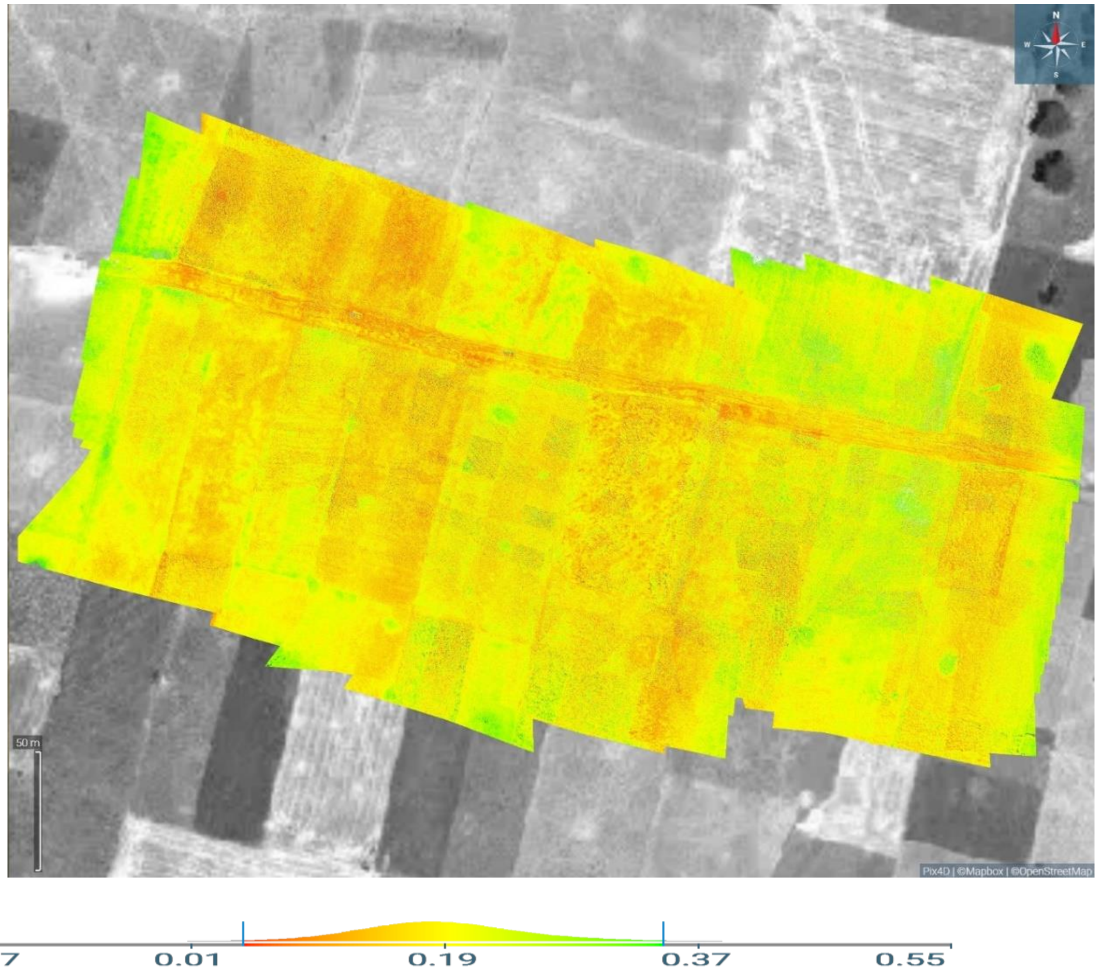


Figure 4.16. Normalized Difference Red Edge Index map

The flight characteristics of parrot blue grass, the relationship among: -time between shot(s), flight height, speed of flight, distance between flight lines and over lap

Altitude (flight height) and spatial resolution do have a high correlation, directly proportional to each other.as altitude increase, the spatial resolution in number increases that means the quality of the image feature visibility decreases but when altitude flight decrease feature visibility is fine and results high spatial resolution of crop image. In case the area coverage is reverse which mean that at high altitude flight the more area covered while at low altitude small area scale capture within high spatial resolution. As altitude, increases and the speed of flight increases the time between shot (s) increase i.e., the time between shot(s) slowly capture the image and reverse when altitude and speed of flight decreases. As flight altitude and distance between flight lines increases, the overlap decreases while as flight altitude and distance between flight path decreases overlap increases. In general overlap do not have any more influence in image capture and it is fixed by the interest of the pilot or user during flight. The whole parameters relations are clearly shown in (figure 4.18) below.

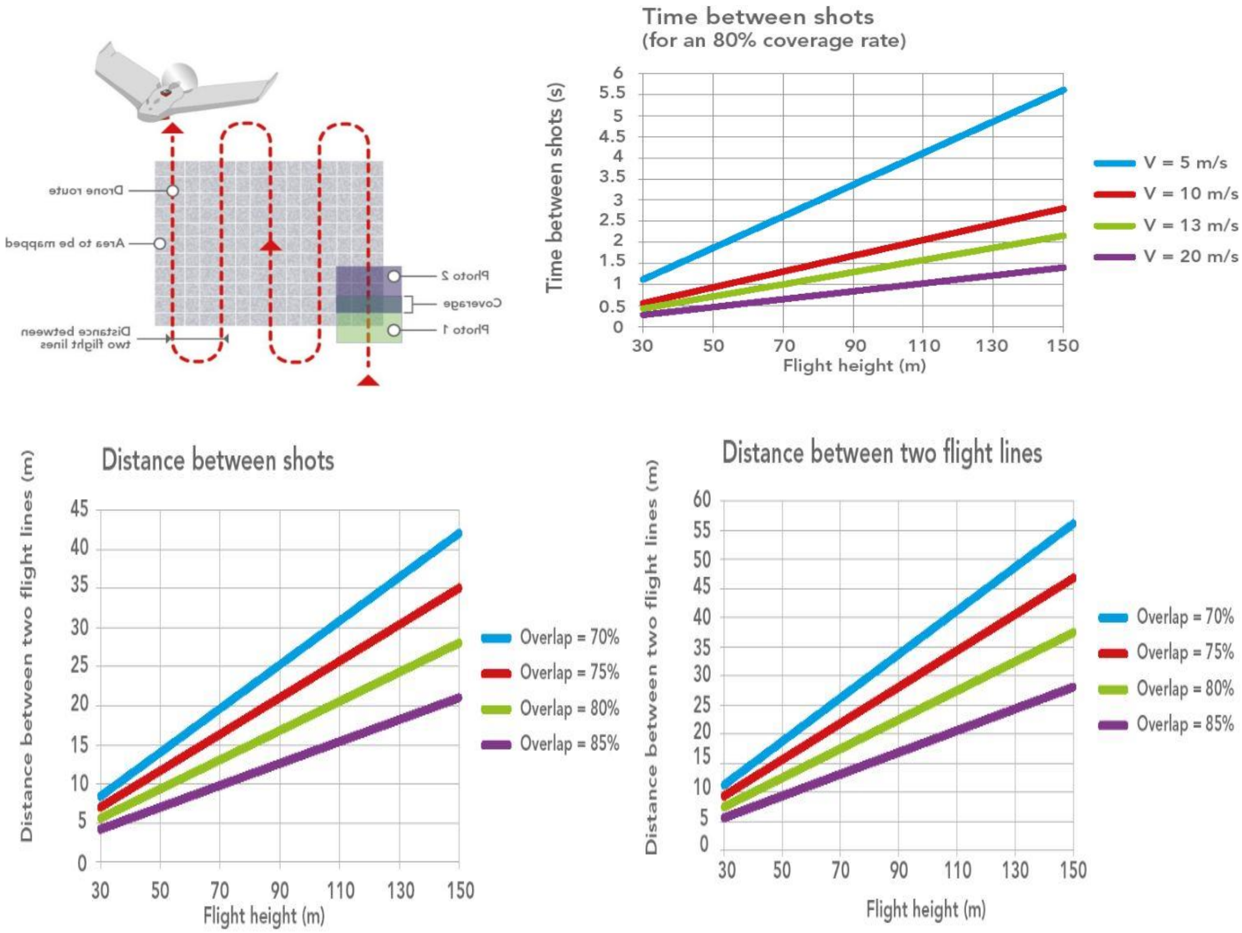


Figure 4.17. The relation parameters of Distance, speed, altitude, shot(s), and overlap

Chapter Five
5. Discussions

5.1 Discussion

In crop image classification, there are different machine-learning algorithms, in this study the supervised Random forest and the traditional Maximum likelihood classification have used. RF algorithm is selected because of its high performance in classifying raster images and fragmented crop type landscape components. Sentinel 2A and UAV has been fused together using Gram Schmidt (GS) technique for crop type mapping using Random forest algorithm and Maximum likelihood classification method. The accuracy assessment evaluated for each classification approach to determine the best method, bands, and sensor to use when classifying crop type in heterogeneous landscape of the cluster farmland. From the fused approach, the Random forest classification algorithm obtained high classification accuracy 94%, the maximum likelihood classification accuracy was 90 % and from UAV data 84% using Random forest. This is showing that Random forest classification in fusion approach have high capability of the moderate spatial and spectral resolution of the data in accurately identifying and distinguishing the diversified crop type mapping i. Regarding the performance of the classifier, it was observed that RF algorithm produced high classification accuracy and it was for field-based crop classification using multispectral data. The study emphasized that RF is effective and accurate means for agricultural crop identification and mapping. The classification was not done only from multispectral image based of the fusion; it needs ground data. Ground truth data has been collected during field survey for each crop type pattern in the plot. These truth data were categorized into testing data and validation. This was to keep up the methodology and also the machine learning require such splitted data to test and verify the classification correctly. In addition to training and validation of ground truth data photos of the sample plots of each crop type was taken using GPS Oregon, these photos were used for classification in association within ground data of the crop type.

In the study, The NDVI of sensors was determined that it is a little bit different in between both UAV and Sentinel 2A. The four-day acquisition date differ the NDVI values in the study area. This shows that as the date between the acquisition data differ the NDVI also tends vary, this means the vegetation growth (from seedling-high spectral reflectance) going to maturation as time goes and the spectral reflectance of each crop decreases when harvesting. Regarding fusion image, The NDVI correlation shows how much the classification of fused image was strong and appropriate classification using RF.

Different software's have been used like pix4Dfield, ERDAS, R, ArcGIS, Agisoft. In case of pix4Dfield preprocess of the raw image have been done and "zonal prescription "that it categorizes and /or classify the study area into regional plots of farmlands automatically shown in figure below. The purpose of categorized area is to know the high spot areas of diseases, stress. That it helps for advisory services. After classify the spots there is an option that you give any value input then it automatically distributes the amount of herbicide or any chemical needed for each categorization. To spray the herbicides no man power needed, the tractor or UAV itself communicates with this system and directly it delivers on each plot category accordingly.

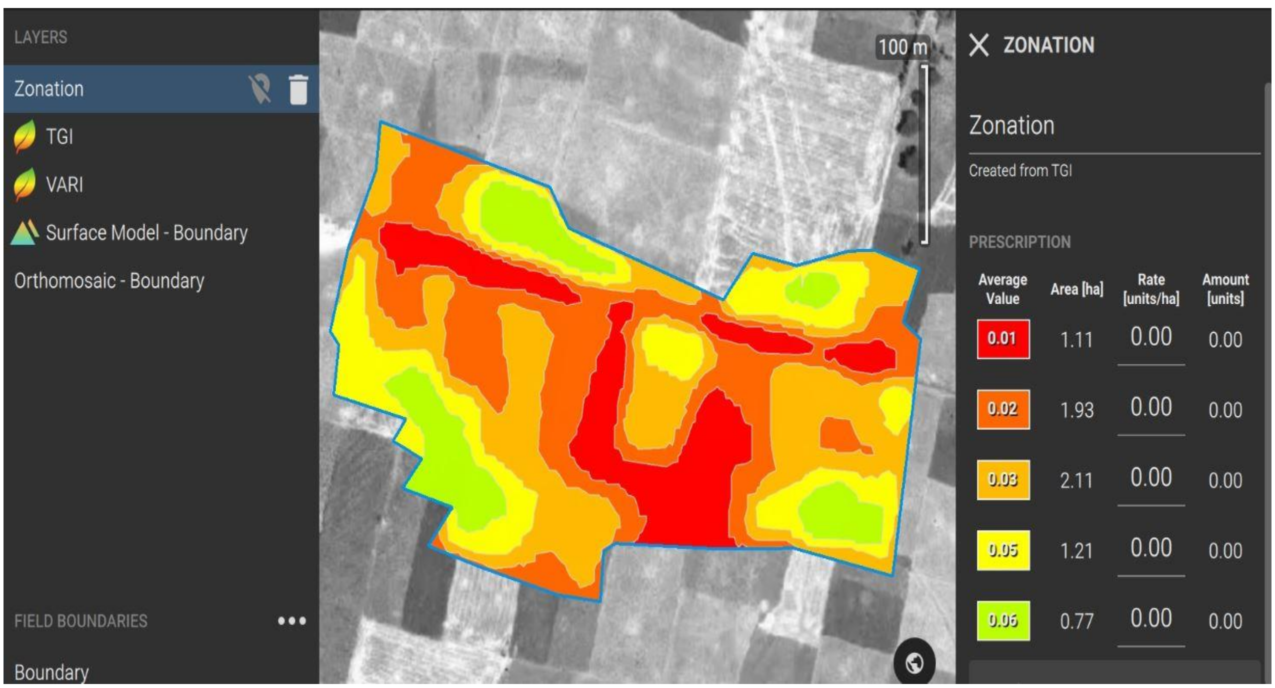


Figure 5.1. Zonal statistics of UAV

In general, the Random forest algorithm produced very good results and the accuracy assessment was very good. Firstly, the main emphasize of this project was to know the potential of Blending of UAV ad Sentinel 2A for crop type mapping. The fused image, the pixel size of UAV improves the sentinel 2A (the low resolution) data. Classifying at high spatial resolution produces the very highest accuracy for crop type mapping and both sensors (UAV and S2A).

Most of the literature states that very similar results can be obtained from both classification approaches when a non-complex scene is being used, however if the scene is complex then RFs are superior. Maximum likelihood has been around for a long time and has been research extensively. It can offer satisfactory results and is easy to perform. Random forests are newer in comparison and offer a power full approach for remote sensing classification approach. Random forest classification uses a large number of decision trees to get the result. Each tree is created using random sample selection A random subset of input predictors is used at every tree to split it making new node. The results gathered from the majority vote created by all the trees in the process.

Overall, it was concluded that the fusion of UAV and S2A approach performs better than separate sensors in discriminating crop type classes and co-existing crop type classes in heterogeneous landscapes because of its high spectral and spatial resolution (Taona, 2019)

Chapter Six

6. Conclusion and Recommendation

6.1 Conclusion

In context of blending of UAV and sentinel 2A of crop type classification, the main objective was to evaluate the potential of blending of UAV, sentinel 2A imagery for crop field classification of multispectral image data set for crop type mapping, and assess the methodology developed. Another ambition was to understand the potential of fused image for classification. Both UAV and sentinel 2A images was a multispectral image, were tested and used in image classification process, while the study area consisted mostly diversified crop field.

The classification of the fused image performed well, with advanced machine learning Random forest to identify and discriminate different crop types in the cluster farmland. This algorithm is powerful in classification and runout huge amount of data within high accuracy. The overall accuracy from RF algorithm resulted 94%, this is because of UAV data played a great role in improving the low resolution of sentinel 2A. Indices calculation was also determined, it was escaped that how much the relationship between UAV and S2A. The correlation of NDVI gives how much the fusion approach is fine for crop type classification.

In this study, it showed that the approach of machine learning algorithm supervised Random forest approach for crop type mapping were promising. For future coming research, there is a need to expand the area of interest so that crop diversified mapping and monitoring also can be done at national level, it is better method if employed over the through out of the year of crop growth from planting to harvesting time. Another approach if Ethiopia capable to acquire the more resolution data and fuse within UAV then employing object-based classification in heterogeneous landscape would be further explored.

6.2 Recommendation

The crop type classification using machine learning of Random forest approach of high spatial and multispectral data used provide a reliable information. These used to show that each spectral reflectance in the classification hence giving information for crop classification assessment from fusion technique, that is the most power full in providing information of agriculture of national level monitoring; this is due to reasonable resolution.

Since the NDVI, correlation shows how much the fusion approach is strong for classification is significant, for this small area coverage. It is better way if the area of interest is enhanced in Ethiopian agricultural practices, detect stress and crop type mapping by using blending of UVA with the newly launching satellite of Ethiopia.

However, in this study the interpretation of the outcome especially in Ethiopia regarded as preliminary even though small area covered. Further study needed to explore the use of multispectral imagery of crop type mapping within blending UAV and sentinel 2A in a heterogeneous landscape and fragmented farmland and also high spatial resolution of UAV and S2A.since Ethiopia recently started launching its own satellites, these is another advantage to use it within UAV technology for the country's precision agriculture, crop type mapping and monitoring. From this study, it recommended that, further studies need to develop a technique capable of accurately analyzing and discriminating the crop types found in small agricultural fields in Ethiopia landscape.

Professionals and or Experts of agriculture like researchers, agronomists' individual farmers and investors is better to know the use of UAV. Especially within the use of these technology in order to monitor the spot areas of stressed crop type from the classified one. It is easy way to spray the herbicides automatically in the system to the stressed crop of the heterogeneous landscape and expanded area. Furthermore, now a days the artificial intelligence is highly running so that the study strongly recommend that the agriculture sector should to interact, select the good approach of the algorithms like SVM, OOB, and KNN for crop type mapping and monitoring. From these within the integration of high spatial resolution and the most selective algorithm, we recommend these combinations also used to detect the weed availability in crop type mapping this was the most challenge in this study to detect.

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