

T.R.
GEBZE TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**ANALYZING AND IMPROVING IMAGE PROCESSING
TECHNIQUES VIA UAV AND SATELLITE IMAGES IN
MONITORING PRECISION AGRICULTURE**

WAFI KHAMIS ALI ABDALLA
A THESIS SUBMITTED FOR THE DEGREE OF
MASTER OF ENGINEERING
DEPARTMENT OF GEOMATICS ENGINEERING
GEODESY AND GEOGRAPHIC INFORMATION TECHNOLOGIES PROGRAMME

GEBZE
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THESIS SUPERVISOR
ASSOC. PROF. DR. BAHADIR ERGUN

GEBZE
2020

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FEN BİLİMLERİ ENSTİTÜSÜ

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DOÇ. DR. BAHADIR ERGUN

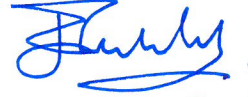
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2020

GTÜ Fen Bilimleri Enstitüsü Yönetim Kurulu'nun 29/01/2020 tarih ve 2020/07 sayılı kararıyla oluşturulan jüri tarafından 06/02/2020 tarihinde tez savunma sınavı yapılan Wafi Khamis Ali ABDALLA'nın tez çalışması Harita Mühendisliği Anabilim Dalı Jeodezi ve Coğrafi Bilgi Teknolojileri Programında YÜKSEK LİSANS tezi olarak kabul edilmiştir.

JÜRİ

ÜYE

(TEZ DANIŞMANI) : Doç. Dr. Bahadır ERGÜN



ÜYE

: Doç. Dr. Cumhuri ŞAHİN



ÜYE

: Doç. Dr. Himmet KARAMAN



ONAY

Gebze Teknik Üniversitesi Fen Bilimleri Enstitüsü Yönetim Kurulu'nun

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SUMMARY

The agricultural sector is very important for the economy in which provides human beings with basic needs and food. Likewise, within the recent years, precision agriculture (PA) has gained huge attention from governments, institutes, and researchers. And as a result, the using of low altitude remote sensing platform in PA has become essential, in which it provides higher Spatio-temporal resolution images comparing to the satellite's one. Thus, applying specific vegetation combinations produces a unique and very useful outputs which helps in farm management and in-field decision making. For this study, an agricultural field near Shendi city (river Nile, northern Sudan) during the 2018 season planted with a Clover implying center pivot irrigation systems (CPIs) have been selected to investigate and analyze the field using remote sensing techniques. For this study, data from satellite and drone images have been downloaded and provided within a short different of time each, and various vegetation indices (VIs) have been applied for the satellite data (Sentinel-2) and the drone images too. Pre-processing procedures applied for the sentinel-2 data (resampling and re-projecting) using SNAP and for the drone data (mosaicking and orthorectification) using Pix4D subsequently. Then five visible VIs, and three infrared VIs have been calculated using ENVI, and qGIS software. Results showed that the normalized difference vegetation index (NDVI) that driven from the sentinel-2 with the lowest standard deviation (StdDev= 0.17) and the red green vegetation index (GRVI) from the drone (StdDev= 3.98) interpret the field and gave results better than the other indices. Results have been evaluated and recommendations for future works also have been made.

Key Words: Precision Agriculture, Sudan, Sentinel-2, UAV, Vegetation Indices.

ÖZET

Tarım sektörü, insana temel ihtiyaç ve gıdaları sağlayan ekonomi için çok önemlidir. Aynı şekilde, son yıllarda, hassas tarım (HT), enstitüler, hükümetler ve araştırmacılar tarafından büyük ilgi görmüştür. Ancak, HT'ta alçak irtifa uzaktan algılama platformunun kullanılması, uydununkiyle karşılaştırıldığında daha yüksek mekan ve zamansal çözünürlüklü görüntüler sağladığı için zorunlu hale geldi. Bu nedenle, belirli bitki örtüsü kombinasyonlarının uygulanması, çiftlik yönetimi ve saha içi karar verme yardımcı olan benzersiz ve çok kullanışlı bir çıktı üretir. Bu çalışma için, uzaktan algılama tekniklerini kullanarak tarlayı araştırmak ve analiz etmek için, Yonca 2018 mevsiminde Şendi şehri yakınında (Nil Nehri, Sudan kuzeyinde) bir tarım alanı seçilmiştir. Bu çalışma için, uydu ve dron görüntülerinden gelen veriler, her biri kısa bir süre içinde indirilmiş, ve ikiside için uydu verileri (Sentinel-2) ve dron görüntüleri pek çok bitki indeksleri (Bİ) uygulanmıştır. Ön-işlem prosedürleri SNAP kullanılarak sentinel-2 verileri (yeniden örnekleme ve yeniden projelendirme) ve dron verileri için Pix4D kullanılarak (birleştirme ve ortorektifleştirme) için uygulanmıştır. Ardından, beş görünür Bİ ve üç kızılötesi Bİ ENVI ve qGIS yazılımları kullanılarak hesaplandı. Sonuçlar, sentinel-2'den çıkan normalize edilmiş farklı bitki örtüsü indeksinin (NEFBÖİ) en düşük standart sapma ($\text{StdDev} = 0.17$) olarak, ve dron'dan kırmızı, yeşil bitki örtüsü indeksi (KYBÖİ) standart sapması ($\text{StdDev} = 3.98$) tarlayı yorumladığını ve diğer indekslere göre daha iyi sonuçlar göstermiştir. Sonuçlar değerlendirildi ve gelecekteki çalışmalar için önerilerde bulunuldu.

Anahtar Kelimeleri: Hassas Tarım, Bitki Örtüsü İndeksleri, Dron, Sudan, Sentinel-2.

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LIST of ABBREVIATIONS and ACRONYMS

<u>Abbreviations</u>	<u>Explanations</u>
<u>and Acronyms</u>	
AI	: Artificial Intelligence
CAA	: Civil Aviation Authority
CPIs	: Center Pivot Irrigation system
CSM	: Crop Surface Models
DNs	: Digital Number(s)
DoD	: Department of Defense
EVI	: Enhanced Vegetation Index
GIS	: Geographical Information System
GLCM	: Grey Level Co-occurrence Matrix
GRVI	: Green-Red Vegetation Index
ICAO	: International Civil Aviation Organization
IoT	: Internet of Things
IT	: Information Technology
LAI	: Leaf Area Index
MRGVI	: Modified Red Green Blue Vegetation Index
NDVI	: Normalized Difference Vegetation Index
OBIA	: Object-Based Image Analysis
PA	: Precision Agriculture
RGB	: Red Green Blue
RGBVI	: Red Green Blue Vegetation Index
RPAS	: Remotely Piloted Aerial System
SAVI	: Soil Adjusted Vegetation Index
SfM	: Structure from Motion
SSCM	: Site-Specific Crop Management
TIFF	: Tagged-Image File Format
TGI	: Triangular Greenness Index
UAVs	: Unmanned Aerial Vehicle(s)
UASs	: Unmanned Aerial System(s)

UK	:	United Kingdom
US	:	United State
UTM	:	Universal Transverse Mercator
VARI	:	Visible Atmospheric Resistant Index
VI _s	:	Vegetation Index(s)
VI _{SNIR}	:	Near Infrared Vegetation Index(s)
VI _{RGB}	:	Visible Bands Vegetation Index(s)
WGS84	:	World Geodetic System 1984
YP	:	Yield Prediction

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1. INTRODUCTION

The agricultural sector is very important for the economy that provides human beings with basic needs and food. Thus, advances in science and technology have made a new revolution in all majors and fields [Kumar and Probha, 2014]. To face the demand in food and improving water usage levels, new technologies have been introduced to agricultural field such as internet of things (IoT), big data and artificial intelligence (AI) which have already been deployed on many farms applications such as farms-connected tractors [Gevaert, 2014], [Dakkak-Arnoux et al., 2018], [Maes and Steppe, 2019].

Nowadays geomatics techniques have become a unique tool for agriculture by utilizing these new techniques, which became a necessity rather than an option [Sylvester, 2018]. Within the growing interest in using these new techniques, the solutions regarding difficult problems have been easily, quickly, and accurately identified and solved [Laliberte and Rango, 2011], [Kumar and Probha, 2014].

Unmanned aerial craft is an additional revolution of technology to serve the people [MD Sayem, 2017]. Moreover, using these unmanned aerial vehicles (UAVs) which has the advantages of providing images with the ultra-high spatiotemporal resolution is becoming fundamental [Laliberte and Rango, 2011], [Gevaert, 2014]. Furthermore, historically UAVs were developed for military purposes only, where we're used to avoiding risking pilots lives when flying over the enemy lines [Whitmore, 2016], [Capolupo, 2016,], [MD Sayem, 2017].

Numerous names and acronyms have been proposed and used to describe these unmanned objects, such as unmanned aerial systems (UASs) which were adopted by the department of defense (DoD) of the united state (US) and the civil aviation authority (CAA) of the united kingdom (UK), other names are drones, and, remotely-piloted aerial system (RPAS) which introduced by the international civil aviation organization (ICAO) [Remondino et al., 2015], [Capolupo, 2016], [Whitmore, 2016], [MD Sayem, 2017]. Accordingly, the most popular terms are UAVs and drones [Gevaert, 2014], [Whitmore, 2016].

The certain trend of the UAVs in the agricultural field can be understood via the existing model of "Technology Push and Market Pull" to help and manage UAVs innovation process. By means, the concept stated that technology pushes a new

invention to the market through research, development, production, and sales. And the market pull implies that in response to an identified market needs [MD Sayem, 2017].

Traditionally, it used to be that balloons, aircrafts, and satellites were the only platforms produce imagery product, but their spatiotemporal resolution limits the requirement of crop growth monitoring (due to cloud cover and other effects) [Hunt et al., 2005], [Remondino et al., 2015], [Chen et al., 2016]. With the ability of coming in a wide range of shapes (multi-rotor, single-rotor, and fixed-wing) and sizes (from tiny to very large), UAVs platforms can provide a very high-resolution images (up to cm-levels) at any time offering a great opportunities for the precision agricultural domain, forestry management, and geosciences [Remondino et al., 2015].

Elsewise, it allows to obtain much quantitative observation at a better resolution and lower cost compared with airborne and satellite platforms, also it can be fully or semi-autonomous with the help of specific software systems [Remondino et al., 2015], [Simelli and Tsagaris, 2015], [Dakkak-Arnoux et al., 2018].

With the technological advances taking place around the globe, agriculture cannot be left behind. However, UAVs can be the perfect representer for these technologies, starting from spraying chemicals to solve visibility problems. Compared with satellites remote sensing and aerial photogrammetry, UAVs satisfies the requirements for agricultural purposes because of many reasons starting by elimination risks for the pilot, it is easily and frequently deployed, and it allows reducing the flight altitude which improves images resolution [Simelli and Tsagaris, 2015], [Capolupo, 2016].

Uses of the UAVs is rapidly growing including real-time monitoring, wireless coverage, archaeological applications, mailing services, search and rescue, traffic supervision, delivery of goods, and pollution detection [Dakkak-Arnoux et al., 2018]. UAVs are now gaining significant efforts to increase its flight duration, the payload, and tolerance, to achieve all that many companies introduce UAVs configurations with different flight altitude and autonomy such as: [Simelli and Tsagaris, 2015].

- Large autonomy, high altitude (65000 feet altitude, 35 hours duration, and 1900 lbs payload)
- Medium altitude, long endurance (27000 feet altitude, 30-40 hours duration, and 450 lbs payload)

- Regular use UAVs (15000 feet altitude, 5-6 hours duration, and 55 lbs payloads)
- Small and portable UAVs.

As a drawback and significant limitation, the weights of the sensors must be suitable for mounting on the UAVs. Moreover, related to the regulation of the country, a specific platform configuration needs to be applied [Capolupo, 2016]. Currently, most UAVs used in the agricultural sector are medium-sized (for analysis applications) while larger ones are used to carry loads (for planting or spraying applications). According to Dakkak-Arnoux et al., 2018 we can apply UAVs into the agricultural application in:

- Soil and field analysis: where UAVs are able to produce 3D maps, which are used for designing seed-planting patterns, (i.e., nitrogen-level management).
- Health assessment: it can also be used to generate multispectral images of crops for analyzing and tracking changes in health and maturity.
- Crop monitoring: in the past satellite imagery was the most advanced form of crop monitoring, but some major drawbacks made it not sufficient:-
 - Relatively high cost,
 - In advance ordering,
 - Poor weather impedes data quality.
- Irrigation: UAVs equipped with special equipment can be used to identify parts of a field experiencing “hydric stress” (inadequate of water).

Also, UAVs allows calculating density and health of the crop while growing which enables better crop management, in general, a seasonal usage of UAVs in agriculture can be demonstrated as the following table [Dakkak-Arnoux et al., 2018]:

Table 1.1: The seasonal usage of UAVs in agriculture.

	Spring	Summer	Fall	Winter
Task	-Prepare machinery -Apply fertilizer -Apply herbicide -Till prepare seedbed -Plant seed - Early analysis of soils, tillage, tile, and drainage	-Apply herbicide -Apply fertilizer -Apply fungicide -Apply insecticide -Irrigation management -Stand count and gap analysis -Irrigation management -Observation of growth variability -Assess and observe nitrogen needs -Crop stage monitoring for application timing	-Harvest Crop -Manage & till residue -Apply fertilizer -Land improvement -Pre-harvest: dry down and stand consistency observation -Post-harvest: analysis of soil, tillage, and topography	-Machinery purchases -Input purchases -Insurance Purchases -Assessment of input and machinery performance
UAVs usage	Year-round	Post-rain: tile drainage system analysis	Post-storm: determine wind/hail/flood damage	Post-event: insurance claim documentation

1.1 Aims and Objectives

The aims of this work are to investigate and test the applications of different VIs for monitoring the precision agriculture without using ground measurement, although the absence of the ground data will not allow delivering quantitative response, but the qualitative response can be delivered [Remondino et al., 2015]. The overall objectives of the study are interested in 1) the creation of high-resolution orthophotos, 2) explore the potential of combining Sentinel-2 and UAV images in precision agriculture, and 3) the analyzation and evaluation of the VIs.

1.2. Research Outline

Section-2 of this research work gives a background overview regarding important concepts in using technologies onto agricultural applications such as precision agriculture, vegetation indices, and yield prediction. Section-3 dedicated on exploring the study area, and the imagery data that will be use. Section-4, instead, is related to the series of applications and procedures due to images pre-processing, applying vegetation indices, and post-processing. Section-5 interpret the results from the above-mentioned applications and discuss them. In the last section, Section-6, the final conclusions and recommendations are presented.

2. BACKGROUND

2.1. Precision Agriculture (PA)

Over the last decades, the strategies of agriculture have changed dramatically, many of these changes have been driven by either economic decisions or environmental guidelines, however, growers now have concerns over gaining nutritional values and high-quality products [Pinter et al., 2003]. precision agriculture (PA) can be defined as a management strategy uses information technology (IT) to an integrated system based on crop information and technologies designed to increase productivity and profits, with fewer impacts on the environment [Ancev et al., 2004], [Zhang and Kovacs, 2012], [Abdullahi et al., 2015], [Remondino et al., 2015].

PA is in general involved with two fundamental technologies which are geographical information system (GIS) and global positioning system (GPS) [Abdullahi et al., 2015]. Also, it differs from traditional agriculture by allowing immediate action on farm management [Lopez et al., 2015]. The PA cycle involves many activities from obtaining the images to generate yields map, weeds, and topography, applying fertilizer, watering (irrigation), and then obtaining the result for implementation [HAN-YA et al., 2010], [Abdullahi et al., 2015].

Because of its early use by the US agricultural adjustment administration, applying PA helps to detect the differences in crop growth and soil condition within the spectral responses [Zhang and Kovacs, 2012]. Also, PA can be viewed closely to site-specific crop management (SSCM) which defined as “Matching resource application and agronomic practices with soil and crop requirements as they vary in space and time within a field” [Ancev et al., 2004].

After its evolvement with the advancement of technology, recently UAVs have become the trend and the most useful tool within the PA [Kumar and Probha., 2014], [Ahmed et al., 2016], by making it possible and easy to acquire real-time images which are so helpful in the decision-making process. PA helps the farmers to outcome the major threats due to the emergence of various pests and diseases in the crop [Kumar and Probha., 2014].

The aim of PA approaches is to improve yield quality while reducing waste and costs to the minimum levels [Comba et al., 2019], by quantifying both temporal and spatial variations of crop conditions which is essential for PA applications [Gevaert, 2014], although it is straightforward intuitive, but PA faces limits in adoption to farming practice by training, costs, and time availability of the imagery [Ancev et al., 2004], [Hunt et al., 2005], these lack of practical applications are a result of various factors such as the difficulties of information collection for the SSCM, the not willingness of farmers to incur the costs, and the gains are usually distributed among a whole range of stakeholders [Dakkak-Arnoux et al., 2018].

Many researchers studied the agricultural applications using UAVs such as crop biomass and nutrient status have been determined using radio-controlled model aircraft as a low-cost platform for remote sensing. However, more work is required to optimize the system and eliminate the assumption that has been made by Hunt et al., 2005.

Likewise, a methodology based on the fusion of UAV image and optical satellite data has been proposed by Ahmed et al., 2016 which opened up the prospects for within-class classification, which is an important aspect for precision agriculture monitoring. Laliberte and Rango., 2011 analyze the sub-decimeter imagery acquired with a UAV over arid rangelands using classification tree analysis in conjunction with object-based image analysis (OBIA).

2.2. Vegetation Indices (VIs)

Vegetation indices (VIs) are an algebraic combinations of two or more spectral bands, resulting in highlight vegetation properties such as chlorophyll content, canopy biomass, and absorbed or reflected energy [Remondino et al., 2015], likewise it used to combine, and filter multiple spectral data sets into a single value [McKinnon and Hoff, 2017], by means they used to decrease large data volumes from remote sensing to useful information for management [Hunt et al., 2011].

However, due to the complexity of crop canopies spectral signatures [Pinter et al., 2003], VIs are taking advantage of such characteristics, calculating differences, ratios, or linear combinations between bands to obtain an index which can be related to certain biophysical properties [Pinter et al., 2003], [Gevaert, 2014]. Most VIs are

being used extensively to study various biological parameters quantifiably [Abdullahi et al., 2015].

Applications of VIs in remote sensing of crops was not new. Meyer and Neto, 2008, Kumar and Probha, 2014, Aydin et al., 2017 reviewed the most used images analysis application in the agricultural sector especially for plant growth and health assessment. Many others explored different spectral bands and their combinations for crop and weed detection [Meyer and Neto, 2008].

Leaf area index (LAI) which defined as the ratio of one-sided green area to the ground area (m^2/m^2) [Gitelson et al., 2003], [Hunt et al., 2005], can play an important role in climate modeling and yield forecasting. Gitelson et al., 2003 introduced a new technique to estimate LAI using the reflectance in the green and the red edge, or the near infrared bands only, as a result, they found that the vegetation indices which used were indicative of the phenological stages during rowing and flowering seasons.

Utilizing UAV to collect RGB imagery is quite simple, cost-effective and a direct VIs calculation [Meyer and Neto, 2008], [Bendig et al., 2013, 2015], consequently several studies explore the potential of using RGB imagery-based VIs from consumer grade cameras mounted on UAVs [Bendig et al., 2013, 2015], [Bareth et al., 2016], [Lussem et al., 2017], [McKinnon and Hoff, 2017]. Foremost, RGB sensors are useful for detecting infection severity, using either the reflectance, the vegetation height, or a combination of both together [Maes and Steppe, 2019].

2.3. Yield Prediction (YP)

Yield prediction (YP) plays an important role in the end-of-season observation which integrates the cumulative effect of weather and management practices through the season [Pinter Jr et al., 2003], [Spitkó et al., 2016]. However, there are two general approaches to use remote sensing for YP, either by a direct method in which prediction is totally made by remotely sensed measurement, or indirectly by incorporating remotely sensed measurement into computer simulations [Pinter Jr et al., 2003].

Mainly the quantity of yield from a growing field can be determined by many factors such as the quality, the nutrient supplies of the soil, and the genetic traits of the crops [Spitkó et al., 2016]. Many studies have been used UAVs focusing on establishing empirical regression models [Bendig et al., 2015], [Maes and Steppe,

2019]. to estimate the total aboveground biomass and its photosynthetic activity, which is crucial in YP [Spitkó et al., 2016].

For decades numerous research activities have focused on the development of VIs application to monitor crops status [Bareth et al., 2016]. As of it is relevant to farmers and to the entire agricultural sectors, accurate and early YP have been explored by numerous studies, for example obtaining YP using UAVs-based RGB by applying the structure from the motion (SfM) in plant height, canopy cover and several different VIs [Chen et al., 2016], [Maes and Steppe, 2019]. Also, crop rotation and residue management using optical sensors have been explored by Govaerts et al., 2011.

An unmanned helicopter was used combinedly with satellite images in Japan [HAN-YA et al., 2010] to assess crop spraying and moisture content estimation giving high accuracy and high-efficiency results. Also, Watts et al., 2010 have explored the alternative of UAVs in wildlife and ecological surveys. Gitelson et al., 2002 studied the spectral properties of a wheat canopy and corn with vegetation fraction (VF) from both visible and near-infrared bands.

Chen et al. 2016 used UAVs-based RGB applying plant height and canopy cover approach to assess and model Cotton growth. Furthermore, Lopez et al., 2015 explored the potential of digital image processing and PA technologies for crop diagnosis, as a result, they found that some VIs showed better characteristics than others, but all VIs allows for quantification of plant information. Bendig et al., 2013 introduced A well-established crop monitoring approach which is also used UAVs-based RGB in the generation of multiple crop surface models (CSM) for plant height and biomass estimation.

3. MATERIALS AND METHODS

3.1. Study Area

The area where the drone images were acquired is in Shendi-city, River-Nile state, in the north of Sudan, summer 2016. A field located in the area was selected for the study. The field has the coordinates of 16°37'N, 33°22'E with an approximate area about 625 m². The field was planted as a center-pivot irrigated system (CPIs) with a Clover which is one of the most profitable crops in the region.

The region is full of agricultural projects, which Clover is one of these cultivated crops among others such as Wheat, Soybean, Sesame, and Peanuts. The climate is dry, and the elevation lay around 550 m above sea level. The figure below (Figure 3.1) shows the geographical location of the study area. For detailed show, the red dot (on the left) represents the Clover field in Shendi-city map, the Sentinel-2 represented in true color (upper right), and the UAV-based RGB image (lower right).

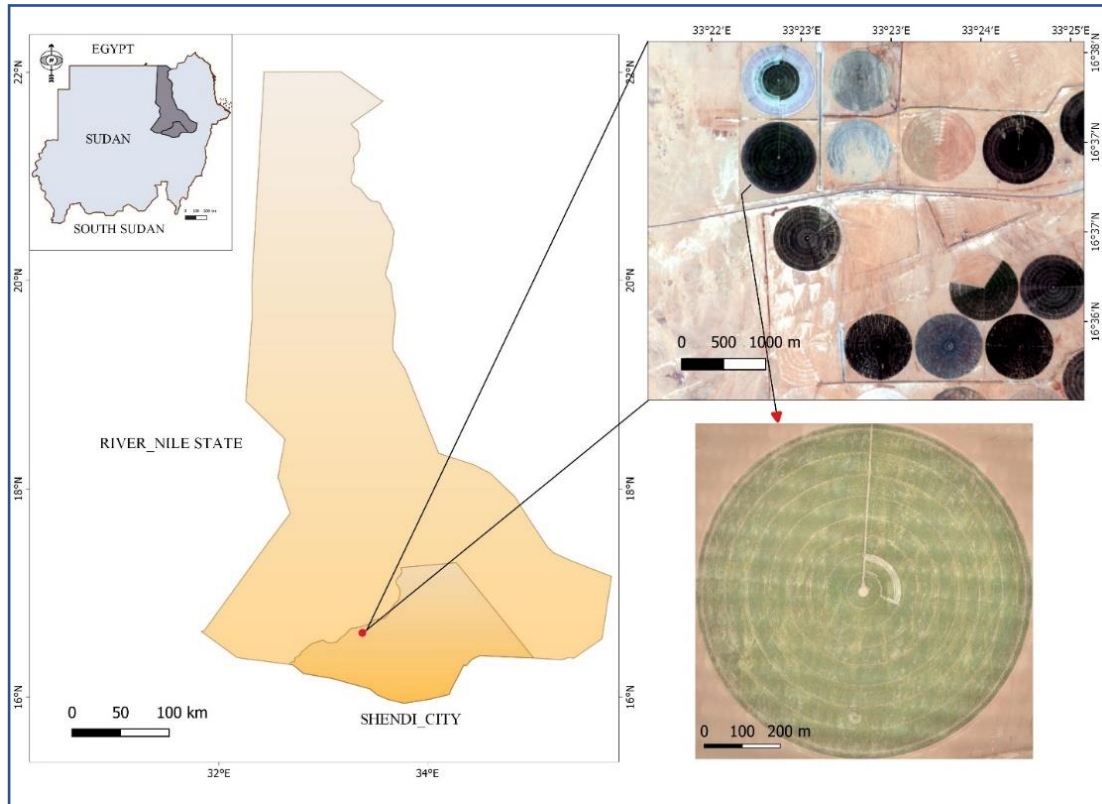


Figure 3.1: The geographical location for the study area. Coordinates are referred to UTM, zone 36N (WGS84).

3.2. Data Used

3.2.1. Drone images

596 sufficiently overlapped Images which were acquired on June 6th, 2018, were provided, the images data acquired using a DJI phantom 4 quadcopter, equipped with a consumer grade FC6310 (f= 8.8mm) RGB camera. Further details regarding the drone images can be found in (Appendix B).

3.2.2. Sentinel-2 Imagery

The sentinel-2 data were provided at a level-1C raw data which comes within 13 spectral bands ranging from 443 nm to 2190 nm and defined between 10m and 60m spatial resolution (Table 3.1). A clear-sky image from Sentinel-2 provided in standard archive format [Verrelst, et al., 2015], [Roy et al., 2016], [Comba et al., 2019] within a repeated cycle of five days have been chosen and downloaded from [Web 2, 2019] for the study. The tile data acquired on June 2nd, 2018 (Data ID: S2A_MSIL1C_20180602T081011_N0206_R078_T36QWD_20180602T115947) covers the region of the study and some neighboring fields.

Table 3.1: Sentinel-2 bands specifications.

Band Name	Central Wavelength (μm)	Spatial Resolution (m)
B1-Coastal	443	60
B2-Blue	490	10
B3-Green	560	10
B4-Red	665	10
B5-Red-Edge1	705	20
B6-Red-Edge1	740	20
B7-Red-Edge1	783	20
B8-NIR	842	10
B8a-NIR-narrow	865	20
B9-Water vapor	945	60
B10-SWIR-cirrus	1375	60
B11-SWIR1	1610	20
B12 -SWIR2	2190	20

4. APPLICATIONS

4.1. Data Pre-processing

The SNAP software [ESA, Sentinel Application Platform, Paris, France] have been used for the Sentinel-2 image, which was re-projected to UTM 36N projection system and re-sampled to the spatial resolution of 10m. Then clipped to the study area. The radiometrically, atmospherically and geometrically corrected UAV images were pre-processed using Pix4D image analysis software [Pix4D SA, Lausanne, Switzerland], which combined all 596 images together into a large rectified mosaic image for the entire study area.

The Desktop used to run the above-mentioned software's included: Intel(R) Core (TM) i5-6500 CPU@ 3.20GHz, RAM: 8GB and GPU: Intel(R) HD Graphics 530 with Windows 10 Pro, 64-bit operating system, further details can be found in the Pix4DMapper quality report [Appendix B]. The imagery block from the UAV was orthorectified and geo-registered. Then the obtained results were saved in tagged image file format (.TIFF) at a spatial resolution of (0.03m) which can be used easily with any geographic information system software.

Many researchers pointed out that in the absence of ground measurements by spectro-diameter, the computations of VIs might be based on digital numbers (DNs) which gives a good description of the vegetation condition [Remondino et al., 2015]. Therefore, in this study images from Sentinel-2 and UAV were processed with the band math function in ENVI image processing software [Harris Geospatial, Boulder, CO, USA], by applying three infrared band related VIs for the Sentinel-2 and five visible bands VIs for both (the Sentinel-2 and the UAV). Also, an open source GIS software qGIS [QGIS, Development Team (2019), Geographic Information System, Open Source Geospatial Foundation Project] have been used to calculate the same indices [Abuleil et al., 2015].

4.2. Application of Vegetation Indices

In this work three well known vegetating indices which reported to have a good correlation with biomass and LAI [Bendig et al., 2015] have been examined to prepare statistical comparison. These indices are near infrared dependent indices which are the normalized difference vegetation index (NDVI) [Rouse et al., 1973], the soil adjusted vegetation index (SAVI) [Bendig et al., 2015], and the enhanced vegetation index (EVI) [Javzandulam et al., 2005]. These VIs equations are illustrated in the following (Table 4.1). Another five visible bands dependent indices were also calculated, these indices were the green red vegetation index (GRVI), the modified GRVI (MGRVI), the red green blue vegetation index (RGBVI) [Bendig et al., 2015]. The visible atmospheric resistant index (VARI) [Getilson et al., 2002], and the triangular greenness index (TGI) [Hunt et al., 2011]. These VIs equations are illustrated in (Table 4.2).

4.2.1. Near Infrared Vegetation Indices (VIs_{NIR})

The NDVI is one of the earliest, and perhaps the most first used VIs which shows the difference between the red light reflected from the plants and the near-infrared light. Healthy chlorophyll absorbs the red light and reflects the near infrared light while damaged chlorophyll reflects both, and it ranges from -1.0 to 1.0, in which positive values indicate greenness and negative values indicate non-vegetated feature such as water, barren area, ice, or clouds [Abdullahi et al., 2015], [Remondino et al., 2015].

Since it is strictly related to crop vigor [Abdullahi et al., 2015], [Comba et al., 2019], it has been developed to reduce the effects of transmittance, atmospheric radiance, and solar irradiance, to estimate the amount of vegetation, LAI, canopy cover, and biomass [Rouse et al., 1973], [Hunt et al., 2011], but it has some limited such as atmospheric influences, soil reflectance, and saturation [Gevaert, 2014], [Bendig et al., 2015].

Many researchers discussed the relation between the NDVI and the biophysical characteristics, such as Hunt et al., 2005 whose compare the NDVI results from the colored-infrared film with a low-cost camera with NDVI results that obtained from

advanced sensors. Moreover, Spitkó et al., 2016 predicted the expected yield by understanding the connection between NDVI and yield in Maize using GreenSeeker™ to record the NDVI value within different stages, their results showed that the most suitable NDVI value is that recorded after the flowering stage.

Considerable efforts have been made in improving the NDVI and in developing new indices to compensate both atmospheres and soil background [Gitelson et al., 2002], as a result, many indices have been introduced, such as the EVI which was developed to optimize the vegetation signal with improved sensitivity for biomass regions and reduction in atmospheric influences.

Another index is the SAVI which was proposed basing on the NDVI but it includes correction for the soil reflectance which used extensively to study various biological parameters quantifiably for those areas where vegetative cover is poor and the soil surface is exposed, and it ranges from -1.0 to 1.0 with low values corresponding to a little amount of greenness [Abdullahi et al., 2015], [Remondino et al., 2015], [Bendig et al., 2015].

Table 4.1: An appropriate near-infrared vegetation indices (VI_{NIR}) used for Sentinel-2 image.

Name	Formula	References
Enhanced VI	$EVI = 2.5 \times \frac{(NIR-R)}{(NIR+(6 \times R)-(7.5 \times B)+1)}$	Javzandulam et al. 2005
Normalized Difference VI	$NDVI = \frac{NIR-R}{NIR+R}$	Rouse et al. 1973
Soil Adjusted VI	$SAVI = \frac{1.5 \times NIR-R}{NIR+R+0.5}$	Bendig et al. 2015

4.2.2. Visible Bands Vegetation Indices (VI_{RGB})

The GRVI has the potential for biomass estimation, which is used as a phenology indicator by which the difference between green and red bands differentiates between the plants and the soil, also it exploits the reflectance in the green band and absorption in the red band through plants chlorophylls respectively [Gitelson et al., 2002], [Hunt et al., 2005, 2011], [Bendig et al., 2015].

To amplify the differences between red, green, and blue, Bendig et al., 2015 has developed two new VIs, one is MGRVI which defined as the normalized difference of

the squared green and the squared red. The other is the RGBVI which defined as the normalized difference of the squared green and the product of (red $\times$ blue) bands. Some researchers found that applying RGBVI in combination with plant height from the CSM might have a similar potential as the NDVI [Bendig et al., 2015], [Lussem et al., 2017].

Table 4.2: An appropriate visible band vegetation indices ($VI_{S_{NIR}}$) used for both Sentinel-2 and the UAV images.

Name	Formula	References
Green Red VI	$GRVI = \frac{(G-R)}{(G+R)}$	Hunt et al.2011
Modified Green Red VI	$MGRVI = \frac{(G)^2-(R)^2}{(G)^2+(R)^2}$	Bendig et al. 2015
Red Green Blue VI	$RGBVI = \frac{(G)^2-(B \times R)}{(G)^2+(B \times R)}$	Bendig et al. 2015
Triangular Greenness Index	$TGI = G - 0.39 \times R - 0.61 \times B$	Hunt et al.2011
Visible Atmospheric Resistant Index	$VARI = \frac{(G-R)}{(G+R-B)}$	Getilson et al. 2002

The VARI was developed at the University of Nebraska by [Getilson et al., 2002], while they were seeking a way to predict VF and monitoring LAI in later stage crops, they noted that the visible bands contained information about VF and LAI throughout the growing season.

Though most indices are calculated using ratios or normalized differences of two or more bands to estimate leaf chlorophyll and plant nitrogen content. Hunt et al., 2011 proposed the TGI to monitor chlorophyll content in leaves based on matrix determinants which defined as the area of the triangle showed in (Figure 4.1).

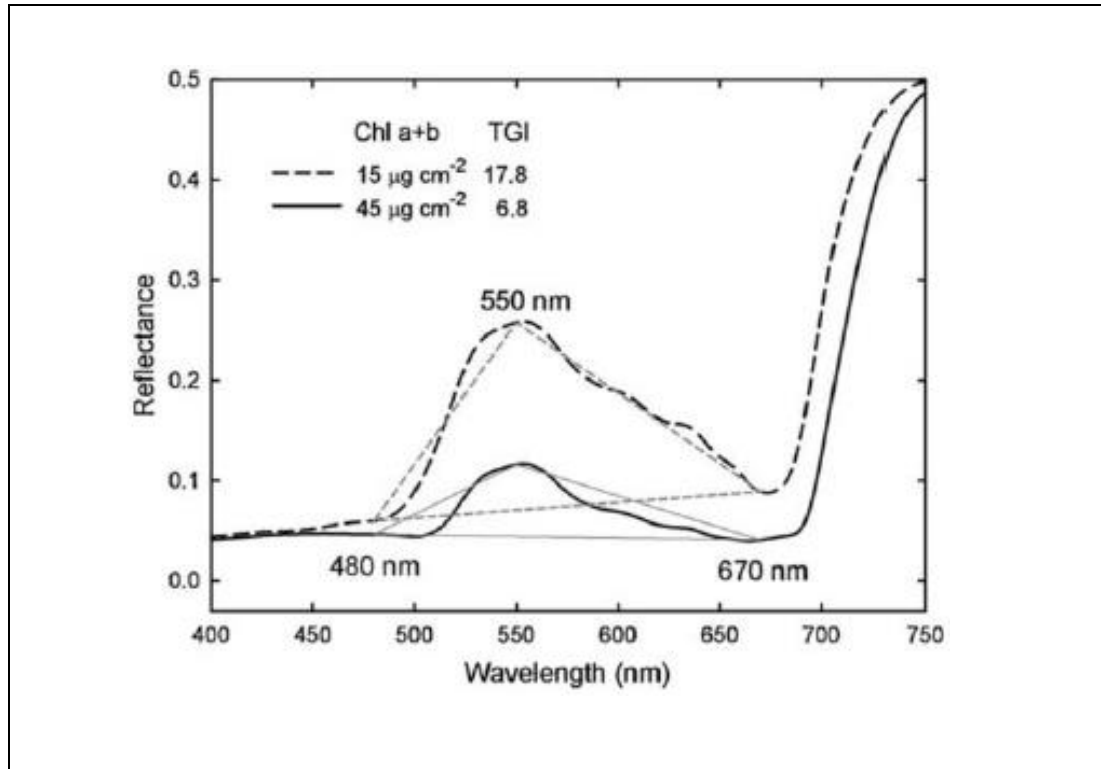


Figure 4.1: The TGI defined as the area between the wavelength 670, 550, and 480nm with narrow bands as shown, or with either broad-band multispectral sensors or digital camera (in which TGI will reduce).

When the green reflectance is greater than the line between the red and blue vertices, the TGI is positive which indicates for the green vegetation. When the green reflectance is less than the red-blue line, then TGI is negative. And it has units of wavelength $\times$ reflectance, so changing wavelength units from nm to μm and changing fractional reflectance to percent reflectance does not affect the result with the conversion of units [Hunt et al., 2011].

McKinnon and Hoff, 2017 recommended that neither VARI nor TGI can be considered a reliable in total crop health indicators and caution should be taken when using them as a replacement for NDVI, also they suggested that it can be reliable when designing VARI for LAI and TGI for chlorophyll only.

Hunt et al., 2005, 2011 calculated the VI_{SRGB} from the orthophotos for crop biomass and nitrogen, and leaf chlorophyll content respectively. Also, Gong et al., 2015 proposed incorporating texture features and robust classifiers (random forest) in the heterogeneous urban landscape to avoid the limitation of low spectral resolution for vegetation mapping, they added grey level co-occurrence matrix (GLCM) to the original RGB image to construct a multi-dimensional feature space.

5. RESULTS AND DISCUSSIONS

In this study, numerous software have been used starting with SNAP software which used for pre-processing sentinel-2 image bands in which re-projecting, and re-sampling are applied, then the resulting image exported to ENVI software for VIs applications and analysis. UAV images in the other hand, have been pre-processed using Pix4D software in which 596 images have been mosaicked then the resulting image exported to ENVI software for further VIs interpretation.

The processes in ENVI were done using the Band Algebra / Band Math tool from the Toolbox window, where VIs parameters were typed directly in the exact popup window. The quick statics showed that, the GRVI from the drone image had an acceptable result with (StdDev = 3.98) among other drone driven indices. On the other hand, the NDVI that driven from the sentinel-2 Image had the lowest standard deviation overall (StdDev = 0.17).

The results of VIs analysis was presented in table 5.1 and representative sample images were showed, where the GRVI from the drone was considered the reference standard, and for the all images indices the same color scale has been used which emulates green and white. The very dark green areas expressed as green color, fading to light green and white for the not vegetated areas in the field. We can notice that the TGI shows the best result in the matter of visual interpretation, but it has an exaggeration in which the field was in the first stage.

Table 5.1: Analysis results of VIs images and histograms

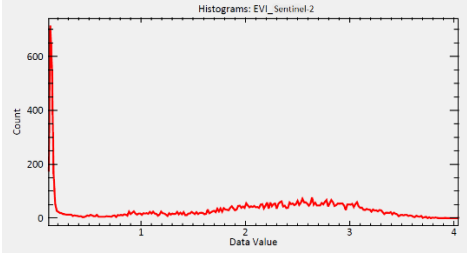
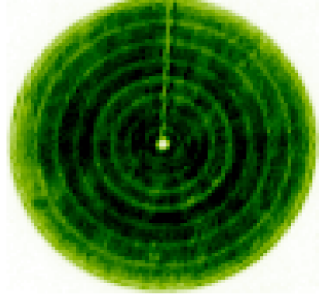
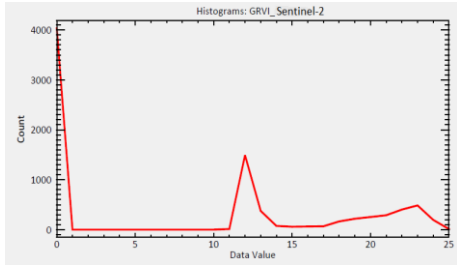
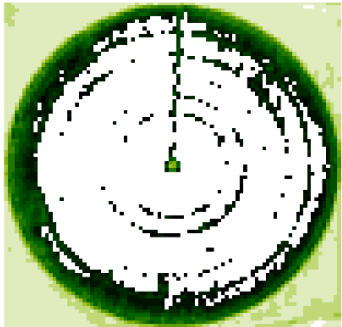
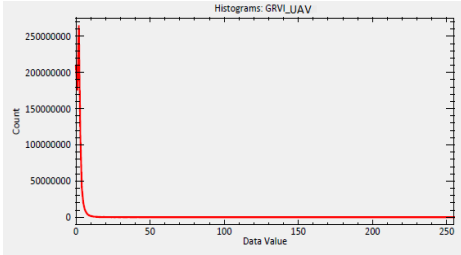
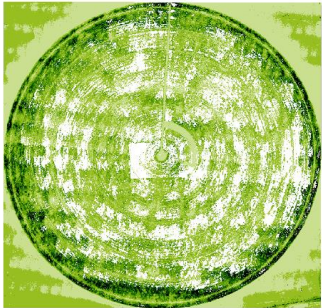
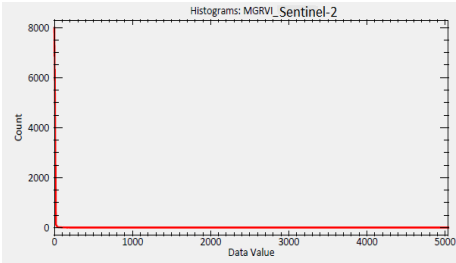
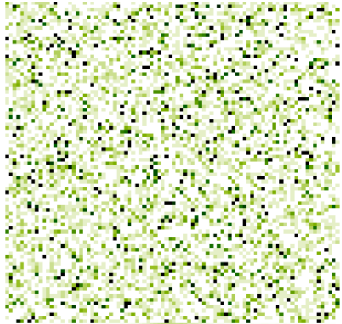
VIs Histograms	VIs Images
1. EVI_Sentinel-2	
	
2. GRVI_Sentinel-2	
	
3. GRVI_UAV	
	
4. MGRVI_Sentinel-2	
	

Table 5.1: Continuation.

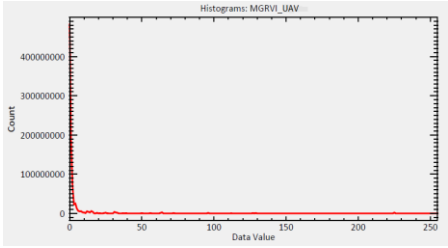
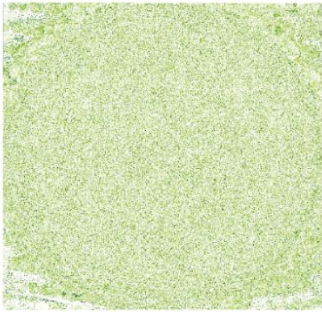
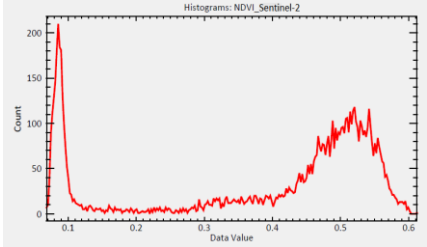
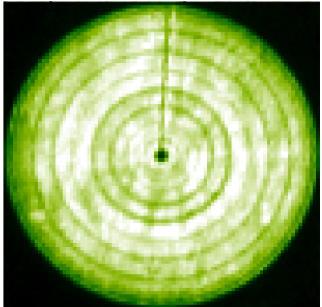
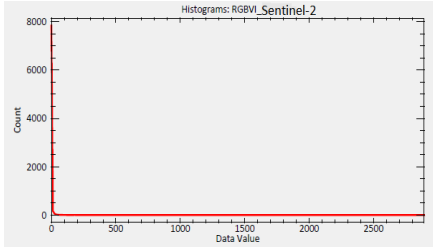
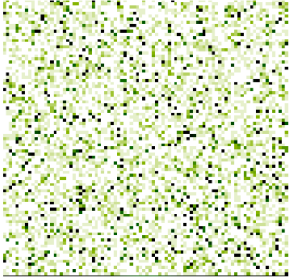
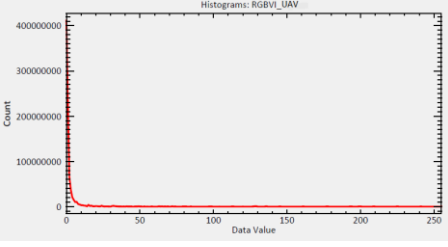
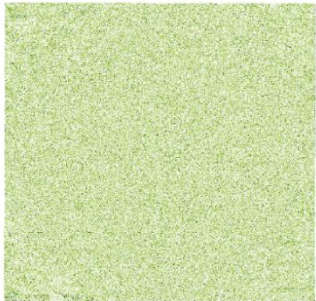
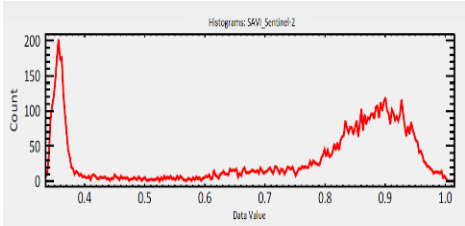
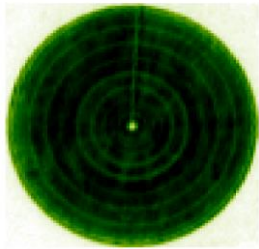
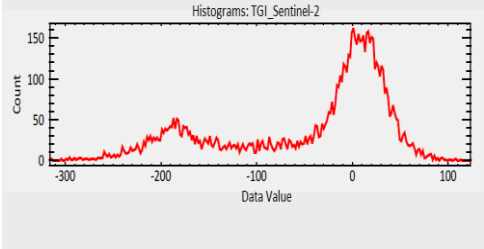
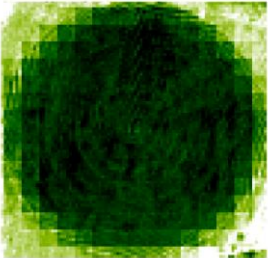
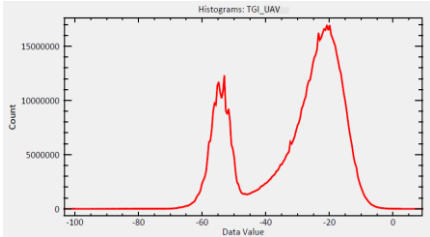
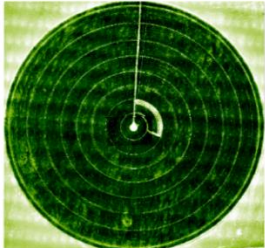
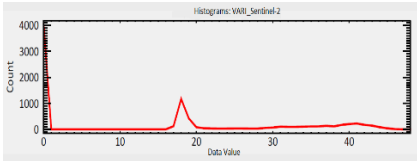
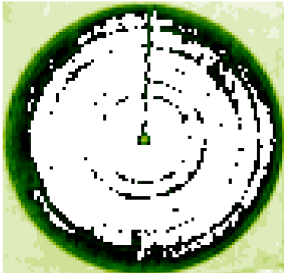
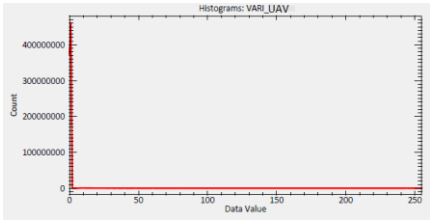
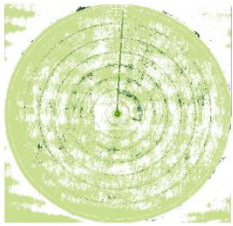
VIs Histograms	VIs Images
5. MGRVI_UAV  The histogram for MGRVI_UAV shows a very high frequency of values near 0, with a count reaching approximately 4,000,000,000. The data values extend up to 250, but the frequency drops significantly after the initial peak.	MGRVI_UAV  The MGRVI_UAV image displays a dense, uniform green field, likely representing vegetation cover from an aerial perspective.
6. NDVI_Sentinel-2  The histogram for NDVI_Sentinel-2 shows two distinct peaks. The first peak is very sharp and occurs at a data value of approximately 0.1, with a count of about 200. A second, broader peak is visible between 0.4 and 0.6, with counts ranging from 50 to 150.	NDVI_Sentinel-2  The NDVI_Sentinel-2 image shows a circular pattern of concentric green rings, suggesting a specific spatial arrangement or artifact in the data.
7. RGBVI_Sentinel-2  The histogram for RGBVI_Sentinel-2 shows a sharp peak at 0 with a count of approximately 8,000. The data values extend up to 2,500, with a long tail indicating a wide range of values.	RGBVI_Sentinel-2  The RGBVI_Sentinel-2 image shows a noisy green field, with many small black and white pixels interspersed among the green pixels.
8. RGBVI_UAV  The histogram for RGBVI_UAV shows a sharp peak at 0 with a count of approximately 4,000,000,000. The data values extend up to 250, with a long tail indicating a wide range of values.	RGBVI_UAV  The RGBVI_UAV image displays a dense, uniform green field, similar to the MGRVI_UAV image, likely representing vegetation cover from an aerial perspective.

Table 5.1: Continuation.

VIs Histograms	VIs Images
9. SAVI_Sentinel-2 	SAVI_Sentinel-2 
10. TGI_Sentinel-2 	TGI_Sentinel-2 
11. TGI_UAV 	TGI_UAV 
12. VARI_Sentinel-2 	VARI_Sentinel-2 
13. VARI_UAV 	VARI_UAV 

The table below gave a better illustration of the different VIs driven from the sentinel-2 and the drone. We can understand from table 3 that, some indices gave very bad result in all means visually and statistically which can be related to the images resolution and the bands different between them.

Table 5.2: the summery statics of the VIs acquired from ENVI stat.

VI / plaform	Min	Max	Mean	StdDev
GRVI_drone	0	255	1.92	3.9863
MGRVI_drone	0	255	2.82	13.68
RGBVI_drone	0	255	3.07	14.4649
TGI_drone	-103.33	9.25	-30.96	14.876
VARI_drone	0	255	2.03	15.4837
EVI_satellite	0.11	4.03	1.81	1.1063
GRVI_satellite	0	25.55	8.86	9.293
MGRVI_satellite	0	5056	4.33	61.641
NDVI_satellite	0.06	0.61	0.39	0.1765
RGBVI_satellite	0	2892.2	4.75	47.973
SAVI_satellite	0.33	1.01	0.73	0.2206
TGI_satellite	-316.16	123.64	-43.11	86.5832
VARI_satellite	0	48.35	14.58	15.971

5. CONCLUSIONS AND RECOMMENDATIONS

In this study a field of Clover has been mapped, then using different image processing software such as Pix4D, SNAP, and ENVI to preprocessing, analyzing, and evaluated the results. various VIs have calculated and compared in which the GRVI from the drone data gave the best result comparing to others, and the NDVI too was the best among the satellite driven ones.

After more than two decades of the sanctions against Sudan in which we cannot access some institutes and companies' resources, even when contacting them, unfortunately, we faced by "this service/product is not available for your country". Soon we are look positively to adopt technologies in many fields especially academics, for the future work we are looking to apply the following to improve the productivity in agriculture by: -

- Adapting and teaching new technologies in our schools and universities,
- Using of different types of cameras lenses such as Fisheye to reduce time and coast.
- Applying multi-campaign flight to establish a time series study.
- Applying Spectro-diameters to get direct spectral signature form field.
- Using the GreenSeeker™ handheld sensor [Verhulst and Govaerts, 2010, Govaerts et al., 2011, and Spitkó et al., 2016].

Future research can involve applying this integrated system on other precision agriculture applications, such as nitrogen detection or crop yield predictions.

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BIOGRAPHY

Wafi ABDALLA was born in El-geneina, west Sudan 1990. He earned his bachelor's degree in geomatics engineering from Sudan university of science and technology, in 2013. He worked in several engineering companies between 2013 and 2015. In the early 2016 he joined the faculty of engineering sciences, El-fashir university as teaching assistant. In the late 2016 he started his graduate studies in Gebze technique university, graduate school of natural and applied sciences, department of geomatics.

APPENDICES

Appendix A: Publication In The Scope Of The Study

Abdalla. W., Ergun. B., (2020), “Analyze and investigate image processing techniques for drone and satellite images in monitoring precision agriculture”, 6th International Conference on Engineering and Natural Science, Sanliurfa, Turkey, 24 -26 January.

Appendix B: Pix4DMapper Quality Report

Table B1.1: Summary, Quality Check, And Calibration Details

Generated with Pix4Dmapper version 4.3.33



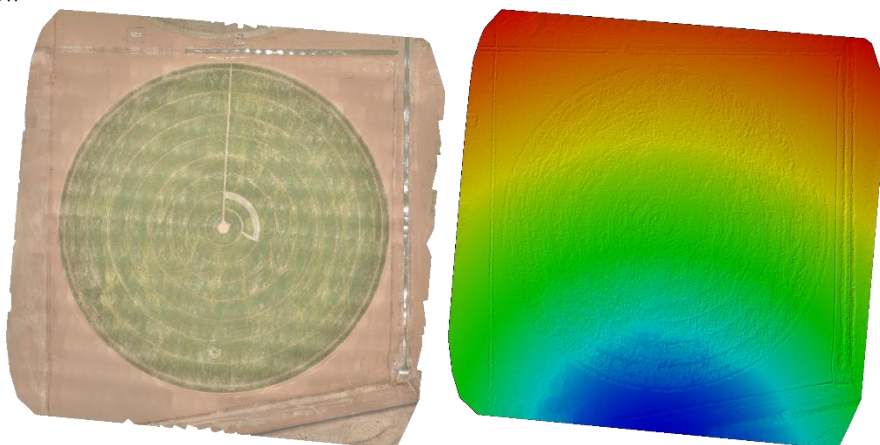
Summary

Project	Wafi_Pix4D_New
Processed	2019-03-28 17:40:47
Camera Model Name(s)	FC6310_8.8_5472x3648 (RGB)
Average Ground Sampling Distance (GSD)	3.03 cm / 1.19 in
Area Covered	1.209 km ² / 120.9390 ha / 0.47 sq. mi. / 299.0014 acres
Time for Initial Processing (without report)	01h:09m:40s

Quality Check

Images	median of 24908 key points per image	
Dataset	595 out of 596 images calibrated (99%), all images enabled	
Camera Optimization	90.52% relative difference between initial and optimized internal camera parameters	
Matching	median of 8134.21 matches per calibrated image	
Georeferencing	yes, no 3D GCP	

Preview



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

Calibration Details

Number of Calibrated Images	595 out of 596
Number of Geolocated Images	596 out of 596

Table B1.2: Initial Image Positions And Computed Tie Points Positions

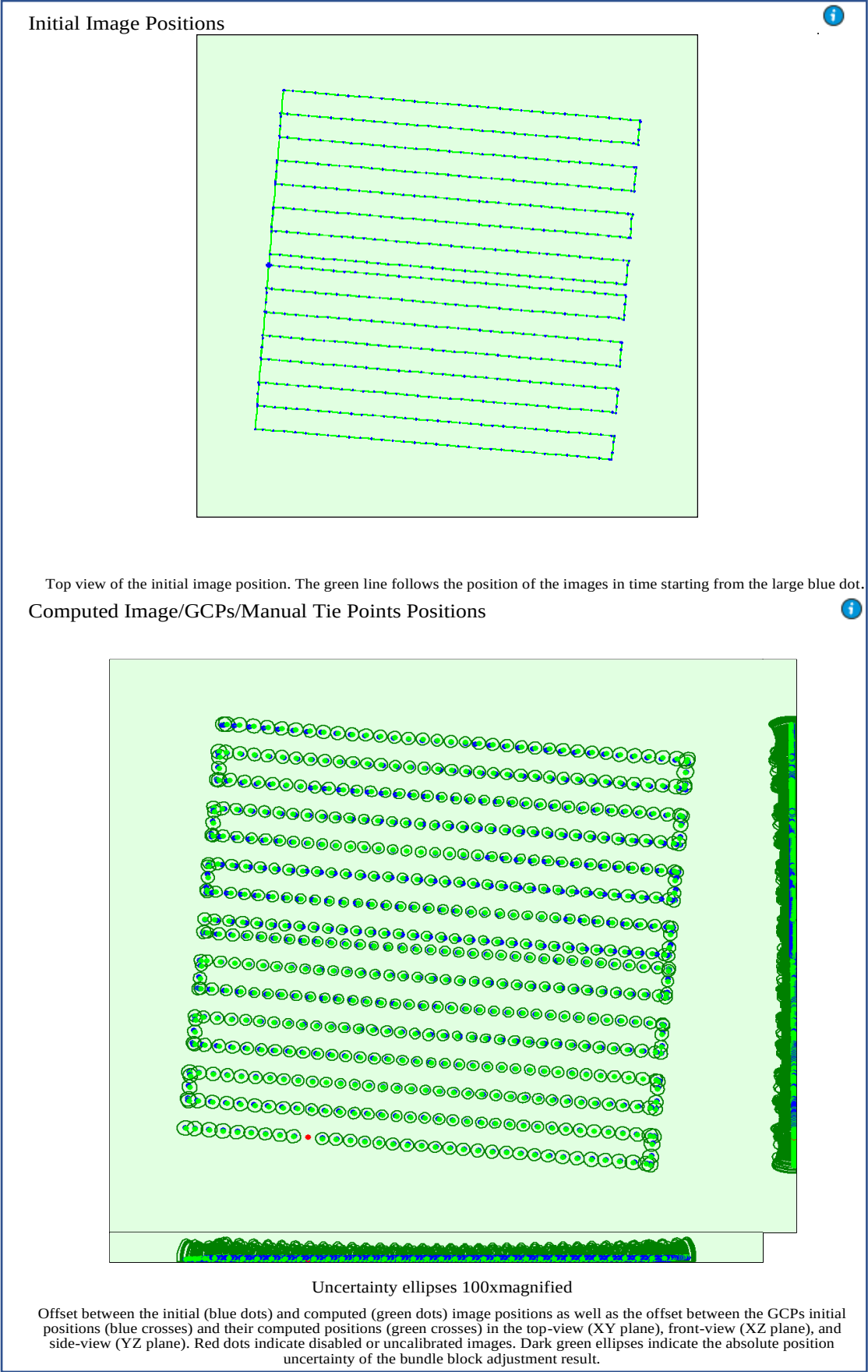
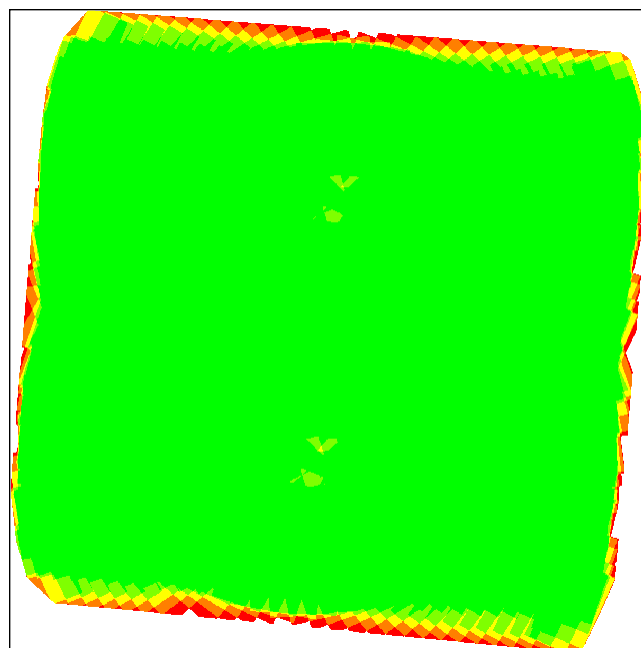


Table B1.3: Bundle Block Adjustment Details

Absolute camera position and orientation uncertainties

	X[m]	Y[m]	Z [m]	Omega [degree]	Phi [degree]	Kappa [degree]
Mean	0.133	0.133	0.293	0.040	0.049	0.014
Sigma	0.016	0.016	0.053	0.008	0.013	0.000

Overlap



Number of overlapping images: 1 2 3 4 5+

Number of overlapping images computed for each pixel of the orthomosaic. Red and yellow areas indicate low overlap for which poor results may be generated. Green areas indicate an overlap of over 5 images for every pixel. Good quality results will be generated if the number of keypoint matches is also enough for these areas.

Bundle Block Adjustment Details

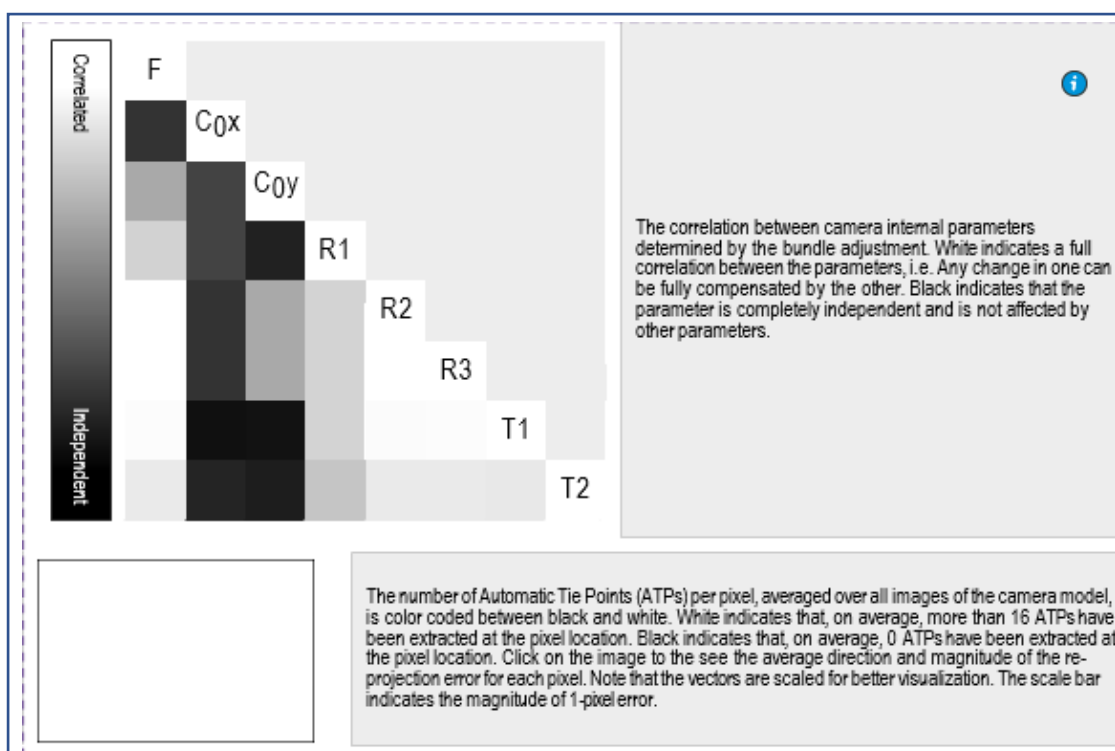
Number of 2D Keypoint Observations for Bundle Block Adjustment	4860782
Number of 3D Points for Bundle Block Adjustment	1710238
Mean Reprojection Error [pixels]	0.204

Internal Camera Parameters

FC6310_8.8_5472x3648 (RGB). Sensor Dimensions: 12.833 [mm] x 8.556 [mm] EXIF ID: FC6310_8.8_5472x3648

	Focal Length	Principal Point x	Principal Point y	R1	R2	R3	T1	T2
Initial Values	3668.759 [pixel] 8.604 [mm]	2736.001 [pixel] 6.417 [mm]	1823.999 [pixel] 4.278 [mm]	0.003	-0.008	0.008	-0.000	0.000
Optimized Values	347.680 [pixel] 0.815 [mm]	2718.431 [pixel] 6.375 [mm]	1786.739 [pixel] 4.190 [mm]	0.000	-0.000	0.000	0.000	0.000
Uncertainties (Sigma)	79.053 [pixel] 0.185 [mm]	1.921 [pixel] 0.005 [mm]	2.057 [pixel] 0.005 [mm]	0.000	0.000	0.000	0.000	0.000

Table B1.4: 2D Keypoints Table And The Generated 3D Points



2D Keypoints Table

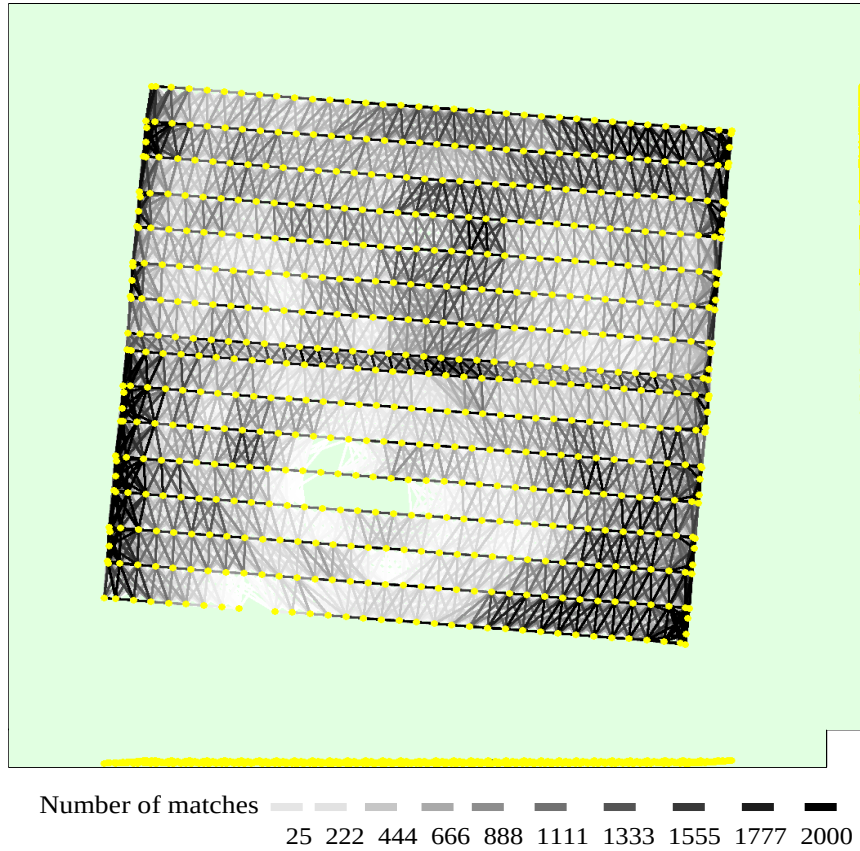
	Number of 2D Keypoints per Image	Number of Matched 2D Keypoints per Image
Median	24908	8134
Min	20015	232
Max	38988	14821
Mean	27833	8169

3D Points from 2D Keypoint Matches

	Number of 3D Points Observed
In 2 Images	1105382
In 3 Images	286953
In 4 Images	122546
In 5 Images	67796
In 6 Images	44882
In 7 Images	31080
In 8 Images	22198
In 9 Images	13609
In 10 Images	7923
In 11 Images	3914
In 12 Images	2026
In 13 Images	1056
In 14 Images	514
In 15 Images	233
In 16 Images	89
In 17 Images	28
In 18 Images	8
In 19 Images	1

Table B1.5: 2D Keypoint Matches And Geolocation Details

2D Keypoint Matches



Geolocation Details

Absolute Geolocation Variance

Min Error [m]	Max Error [m]	Geolocation Error X [%]	Geolocation Error Y [%]	Geolocation Error Z [%]
-	-15.00	0.00	0.00	0.00
-15.00	-12.00	0.00	0.00	0.00
-12.00	-9.00	1.68	0.00	0.00
-9.00	-6.00	6.55	0.00	0.00
-6.00	-3.00	18.15	0.34	0.00
-3.00	0.00	23.03	50.59	52.44
0.00	3.00	24.37	46.22	47.56
3.00	6.00	14.29	2.02	0.00
6.00	9.00	11.09	0.84	0.00
9.00	12.00	0.84	0.00	0.00
12.00	15.00	0.00	0.00	0.00
15.00	-	0.00	0.00	0.00
Mean [m]		-0.000003	-0.000036	0.027750
Sigma [m]		4.436688	1.529888	1.131385
RMS Error [m]		4.436688	1.529888	1.131725

Min Error and Max Error represent geolocation error intervals between -1.5 and 1.5 times the maximum accuracy of all the images. Columns X, Y, Z show the percentage of images with geolocation errors within the predefined error intervals. The geolocation error is the difference between the initial and computed image positions. Note that the image geolocation errors do not correspond to the accuracy of the observed 3D points.

Table B1.6: Initial Processing Details

Relative Geolocation Variance			
Relative Geolocation Error	Images X [%]	Images Y [%]	Images Z [%]
[-1.00, 1.00]	72.27	99.16	100.00
[-2.00, 2.00]	99.50	100.00	100.00
[-3.00, 3.00]	100.00	100.00	100.00
Mean of Geolocation Accuracy [m]	5.000000	5.000000	10.000000
Sigma of Geolocation Accuracy [m]	0.000000	0.000000	0.000000

Images X, Y, Z represent the percentage of images with a relative geolocation error in X, Y, Z.

Geolocation Orientational Variance	RMS [degree]
Omega	0.360
Phi	0.230
Kappa	2.857

Geolocation RMS error of the orientation angles given by the difference between the initial and computed image orientation angles.

| Initial Processing Details | |
| System Information | |

Hardware	CPU: Intel(R) Core (TM) i5-6500 CPU @ 3.20GHz RAM: 8GB GPU: Intel(R) HD Graphics 530 (Driver: 24.20.100.6290)
Operating System	Windows 10 Pro, 64-bit

| Coordinate Systems | |

Image Coordinate System	WGS 84 (EGM96 Geoid)
Output Coordinate System	WGS 84 / UTM zone 36N (EGM96 Geoid)

| Processing Options | |

Detected Template	Ag RGB
Keypoints Image Scale	Full, Image Scale: 1
Advanced: Matching Image Pairs	Aerial Grid or Corridor
Advanced: Matching Strategy	Use Geometrically Verified Matching: yes
Advanced: Keypoint Extraction	Targeted Number of Keypoints: Automatic
Advanced: Calibration	Calibration Method: Alternative Internal Parameters Optimization: All External Parameters Optimization: All Rematch: Auto, no

| Point Cloud Densification details | |
| Processing Options | |

Image Scale	multiscale, 1/4 (Quarter image size, Fast)
Point Density	Low (Fast)
Minimum Number of Matches	3
3D Textured Mesh Generation	no
LOD	Generated: no
Advanced: Image Groups	group1
Advanced: Use Processing Area	yes
Advanced: Use Annotations	yes
Time for Point Cloud Densification	21m:10s
Time for Point Cloud Classification	NA
Time for 3D Textured Mesh Generation	NA

Table B1.7: Digital Surface Model, Orthomosaic And Index Details

Results 	
Number of Generated Tiles	1
Number of 3D Densified Points	4938603
Average Density (per m ³)	11.99
DSM, Orthomosaic and Index Details 	
Processing Options 	
DSM and Orthomosaic Resolution	1 x GSD (3.03 [cm/pixel])
DSM Filters	Noise Filtering: yes Surface Smoothing: yes, Type: Sharp
Orthomosaic	Generated: yes, Merge Tiles: yes GeoTIFF Without Transparency: no Google Maps Tiles and KML: no
Time for DSM Generation	00s
Time for Orthomosaic Generation	02h:58m:33s
Time for DTM Generation	00s
Time for Contour Lines Generation	00s
Time for Reflectance Map Generation	00s
Time for Index Map Generation	00s

Appendix C: Vegetation Indices Results From qGIS

Table C1.1: Visible Bands Vegetation Indices

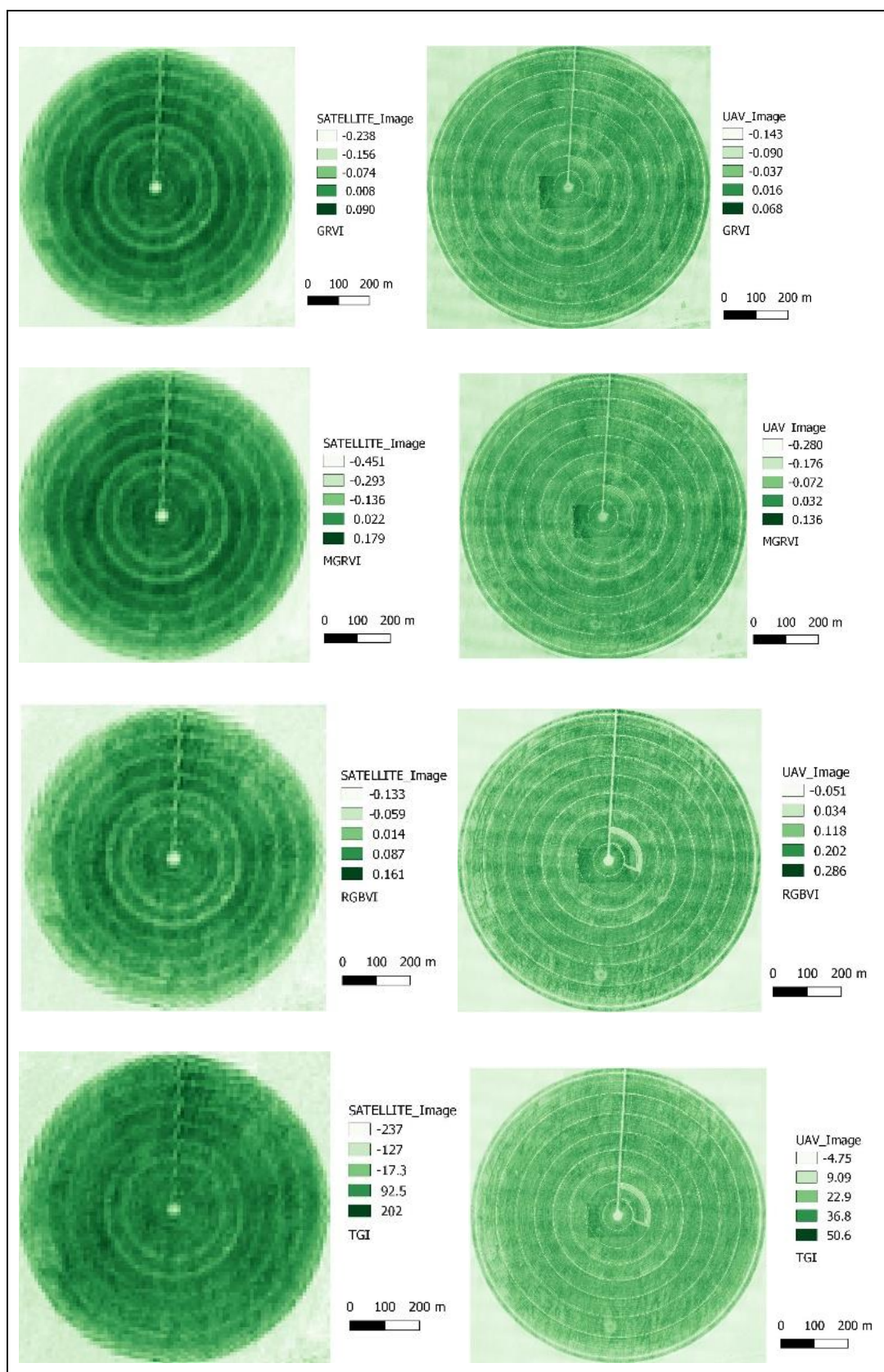


Table C1.2: Infrared Band Vegetation Indices

