THESIS

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Application of remote sensing in agriculture: comparison between manual and UAV methods in data collection.

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ACRONYMS

UAV - Unmanned Aerial vehicle.

UAS - Unmanned Aerial system.

UGV – Unmanned ground vehicle.

DTM – Digital terrain models.

DSM – Digital surface models.

CHM – Canopy height models.

RS – Remote sensing.

TABLE OF CONTENTS.

CHAPTER ONE.

1. INTRODUCTION.

Reports project the global population to reach approximately 10 billion by 2050, furthermore, we anticipate a 70% increase in the demand for food production. Climate change will significantly impact agriculture production, leading to a decline in rural populations and a rise in food waste (FAO, 2022). Meeting these demands will be challenging unless there is a profound shift in the agricultural production model. Research indicates that there are approximately 800 million hungry people worldwide. Current trends predict that by 2030, malnutrition will affect 8% of the world's population, or 650 million people (WHO, 2022).

Meeting these challenges will necessitate a collaborative effort among governments, investors, and innovative agricultural technologies. An alternative effort to overcome these challenges is to adopt emerging technologies in agriculture (Rose & Chilvers, 2018). Agriculture 4.0, also known as'' the fourth agriculture revolution'', which indicates the future of farming technology, is integrating new technologies and innovative services into agriculture, necessitating cultural and behavioral changes among all production stakeholders in order to increase productivity, efficiency, and sustainability. Agriculture 4.0 is expected to use robots, temperature and moisture sensors, aerial imagery, GPS technology, advanced tools, precision farming techniques, and robotic systems (De Clercq et al., 2018). The method applied in data collection determines the quantity of inputs and resources to be applied. Traditionally, farmers apply inputs uniformly, disregarding spatial variations within the field (da Silveira & Amaral, 2022). As a result, the application of inputs turns out to be unnecessarily high, but with the help of advanced technology, farmers can now apply a precise amount of input to specified areas. Agriculture 4.0 encourages the use of advanced technology in data collection which include the use of remote sensing technology to obtain high-quality data, which will eventually enable farmers and researchers to use accurate and timely data for important decision-making strategies (Javaid et al., 2022). This technology enables automation in the monitoring of atmospheric conditions, soil conditions, and crop growth with high spatiotemporal resolution.

Remote sensing technology help to shift from labor-intensive, experience-based decision-making to autonomous, data-driven methods is crucial for enhancing agricultural productivity. Growers can now be aware of future management decisions thanks to real-time field information, while agricultural scientists can fully utilize this data to address significant scientific puzzles (Alahmad et al., 2023). Decision-makers greatly benefit from the application of digital technology in agriculture. This digitalization delivers an extensive amount of data on a farm's environment, resources, technological processes, and produced goods through the utilization of precision tools. We can then use this information to optimize technical decisions, utilizing precise, site-specific technology based on the available data (Milics et al., 2022).

While technology is becoming more important in agriculture, manual data collection remains the oldest and most widely used method worldwide. It is also useful for a variety of agricultural operations. When comparing the two approaches to data collection—the manual data collection method versus employing remote sensing technology, specifically the use of UAVs—significant factors and consequences for agricultural procedures and decision-making protocols will be revealed. Apart from their differences, the two methods differ in terms of flexibility, cost of installation, durability, accuracy, and precision. The two methods raise other important questions, between the two methods;

Qn1. Which method requires a high amount of manpower in operation?

Qn2. Which method is more time-consuming to complete a task in a given area?

Qn3. How does the percentage of work done vary between the two?

The study aims to address the aforementioned inquiries by evaluating two methods and determining which method demands less human labor while delivering efficient results swiftly and cost-effectively. The comparison was made in assessing maize plant height, plot quality and stand count. The study was conducted at the maize testing fields of the Limagrain Seed Company in Germany.

CHAPTER TWO.

2. LITERATURE REVIEW.

2.1. Remote sensing.

Remote sensing is a science and art that involves gathering information about objects or areas from a distance without physical contact. Agriculture remote sensing is a potential technology that enables the observations of crops in a large unit area in a comprehensive, distant and non-interrupted manner. This technology monitors the earth's resources with greater precision and accuracy than ground observations (NASA, 2020). Remote sensing uses the electromagnetic spectrum (visible, infrared, and microwaves) to assess the earth's features. This method generally involves an interaction between incoming radiation and the specific features under study. The electromagnetic radiation that is emitted or reflected by plants is collected by these sensors, which is then processed to generate valuable information (Adjovu et al., 2023).

2.2. Types of remote sensing.

Active remote sensing uses their own emitted source of light or radiation. It uses seasons to detect reflected responses from objects irradiated by artificially generated energy sources, such as radar. Passive remote sensing relies on the reflected source, which enables them to detect the reflected or emitted electromagnetic radiation from natural sources (Aqeel et al., 2011)

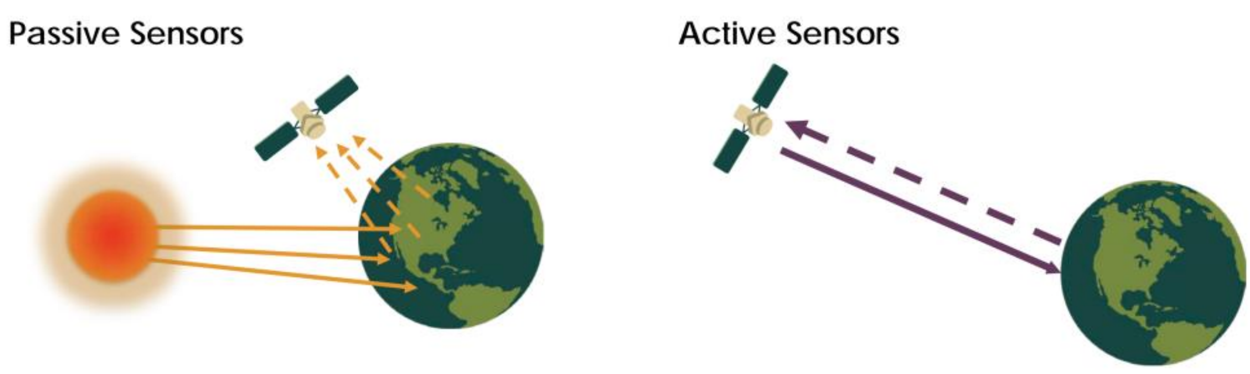


Figure 1. Diagram of active sensors and passive sensors (By: NASA)

These sensing devices are affixed to a specific platform, such as Unmanned Aerial System (UAS), Unmanned Ground Vehicle (UGV) or field robot and satellite, carrying out remote measurement tasks (Balestrieri et al., 2021). These platforms are continuously improving their operational duration, reliability, user-friendliness, and temporal resolution (the time interval between successive remote sensing measurements), which in turn affects the spatial resolution. Because different platforms offer different features, selecting the appropriate platform depends on the type of issue at hand. Spatial resolution, farm size, and operating costs are three key factors to take into account when selecting the optimal platform (Pajares, 2015). Data obtained from remote sensing technologies significantly aids in monitoring surface features by offering timely, comprehensive, cost-effective, and recurrent information about Earth's surface (Omia et al., 2023). According to Ray, (2016) the concept of remote sensing involves six stages:

- Source of electromagnetic energy (EME), sun or transmitter is the source of energy.
- Transmission of energy from the sources to the surface of the earth (as well as absorption & scattering by the atmosphere).
- Interaction of the energy with the objects on the surface of the earth
- Transmission of energy to the remote sensing sensors.
- Generation of the data in pictorial &/or digital form.
- Analysis, interpretation & use of data.

2.3. Importance of remote sensing in agriculture

Remote sensing plays a vital role in this era of modern agriculture, it delivers a range of potentials that contribute to increased efficiency, productivity and sustainability. The technology of remote sensing in agriculture has grown rapidly due to its ability to provide valuable information about environmental conditions, land management practices, and crop health. This technology enables farmers to monitor large fields in a non-destructive way. Farmers can now collect information on a variety of topics, including water stress, pest and disease invasion, crop health, and nutrient levels. Through the availability of this data, farmers can now make well-informed choices concerning irrigation, pest and disease control, fertilisation, and crop management in general. This will eventually lead to productivity enhancement, resource efficiency, and sustainability in the field of agriculture (Victor et al., 2024).

2.3.1. Application of remote sensing in Agriculture.

In its early stages, the primary goal of RS technology was to classify different types of land cover while paying special attention to crop varieties for use in agriculture. However, the primary objective of agricultural RS technology now is to characterize the biophysical properties of plants, which makes RS technology an excellent method for tracking and assessing agricultural practices (Shanmugapriya et al., 2019). There is no need for physical disturbance of the crop since remote sensing provides insights without getting into contact with the element under study. RS technology ensures an economical way of gathering information over a large geographic area. With the application of RS techniques to agricultural canopies, it is very possible to secure important agronomic parameters (Kumar et al., 2021). I reviewed some areas of remote sensing application:

2.3.1.1. Monitoring of vegetation cover.

Several studies used digital image processing and aerial photos to conduct scientific experiments. RS uses digital image processing methods to minimize the required field data collection while maintaining the highest estimation accuracy (Kingra et al., 2016). Hyperspectral data has shown to be more effective than broadband multispectral remote sensing in improving crop and vegetation characterization, discrimination, modelling, and mapping. This is an alternative to traditional field scouting methods for soil and crop assessment. RS technology is inevitable in agricultural activities because it is non-destructive in nature. To describe canopy vegetation, scientists have created a number of spectral vegetation indices (Basso et al., 2004).

2.3.1.2. Nutrient Management.

Nutrient management is a crucial aspect to consider when employing remote sensing technology. By detecting nutrient stresses, remote sensing enables sz ite-specific management practices, thereby reducing cultivation expenses and enhancing fertiliser efficiency (Kingra et al., 2016). Nutrient deficiencies in plants affect the colour, moisture levels, and internal structures of leaves, resulting in changes in reflectance properties. Any nutrient deficiency or fluctuation can cause changes in crop canopies, resulting in noticeable variations in canopy reflectance or temperature. For instance, crops with insufficient nitrogen have significantly higher red (R) reflectance than the (IR) infrared region. As a result, various vegetation indices based on red and infrared reflectance have been developed as spectral parameters for assessing crop canopies under varying fertilization and nutrient conditions (Arr, 2012).

2.3.1.3. Irrigation water management.

The timing and amount of irrigation applied are critical for reducing crop water stress and achieving optimal crop growth and yield. Farmers use a variety of irrigation management methods depending on factors such as water availability, existing farm water infrastructures, local water regulations, economic conditions, farm size, farmer knowledge, and other considerations (Pardossi et al., 2009). Many farmers use uniform irrigation techniques at regular intervals, based on their previous farming experience, soil conditions, and local climate. In contrast, large commercial farmers use soil moisture monitoring systems that can include both wired and wireless moisture sensors. These systems allow for both automated and manual irrigation operations based on real-time soil moisture data and crop- or plant-specific water requirements (Sishodia et al., 2020). . However, these measures are inadequate, as they fail to account for variations within the field and rely on a uniform irrigation rate across the entire field. Remote sensing enables the identification of variations within the field (Evans et al., 2013). Remote sensing images, gathered at multiple points throughout a growing season, are utilized to identify different markers of crop water demand, including ET (evapotranspiration), soil moisture levels, and crop water stress. These markers are then employed to accurately estimate the water needs of the crops and to schedule irrigation accordingly (Ahmad et al., 2021).

2.3.1.4. Pest and Disease Management.

Diseases: Early detection of plant diseases helps to limit their spread and thus prevent significant losses in crop production and farm earnings. Traditional methods, such as field scouting, are inefficient due to their time requirements, reliance on labor, and susceptibility to human error (Ehsani et al., n.d. 2013). Furthermore, identifying diseases in their early stages can be difficult using only manual field scouting, particularly when symptoms are not yet fully apparent. Remote sensing is an effective method of disease monitoring, especially during the early stages of disease progression. Various techniques, including RGB, multi-spectral, hyperspectral, thermal, and fluorescence imaging, have been used to detect diseases in various crop types (Mahlein, 2016).

Pest: Remote sensing is used to evaluate and monitor insect defoliation by correlating variations in spectral responses with symptoms such as chlorosis (leaf yellowing) and foliage reduction over a specific timeframe (W. S. Lee et al., 2010). The technology helps to identify specific pests and differentiate between insect and disease damage to the same crop plant (Riedell et al., 2004).

2.3.1.5. Weed management.

Traditional weed control methods, which typically involve applying herbicides uniformly, are ineffective and increase the likelihood of pesticide runoff, posing environmental risks. (Lameski et al., 2018). Weed control can be achieved through various approaches described in the literatures, RS technology to map weed patches for precise weed management (Weiss et al., 2020). Weeds can be distinguished from intended crop according to their distinct spectral signatures and phenological or morphological traits. The precision and efficacy of machine learning techniques in image classification and weed mapping have been increasing (H. Huang et al., 2020). UAVs (Unmanned Aerial Vehicles) are the preferred technology platform for weed mapping and management (Y. Huang et al., 2018).

2.3.1.6. Crop modelling and production forecasting.

Pre-harvest data on crop production is important in shaping national food policy. Crop yield estimates must be accurate to forecast crop production effectively. The application of remote sensing technology has been utilized to predict crop yields, primarily relying on statistical and empirical correlations between yield and vegetation indices (Bharadiya et al., 2023). RS technology enables to predict crop production and yield in a specific area by assessing the amount that will be harvested under particular conditions. Two types of sensors—infrared (IR) and optical sensors—attached to UAVs can calculate different types of vegetation indices such as the NDVI (normalized difference vegetation index). This index is used to measure nitrogen content, biomass, and chlorophyll, as well as to predict crop yield more accurately, quickly, and without destruction during the process (Széles et al., 2024).

2.3.1.7. Application of remote sensing in phenotyping.

Genotypes determine an organism's genetic composition, specifically its DNA sequences. Plants with the same genotype may exhibit distinct traits depending on their cultivation conditions. Field phenotyping is the quantitative assessment of a plant's anatomical, physiological, and biochemical properties in its natural environment (Pieruschka & Schurr, 2019). When discussing sustainable farming, the focus shifts to sustainable intensification, or, more recently, yield preservation, which necessitates an examination of the entire crop production process. This includes developing and selecting plant varieties that are best suited to specific environmental contexts, as well as improving agricultural land management. A critical component of these efforts is quantitatively evaluating the characteristics of plants that contribute to increased and consistent production, as well as the efficient use of resources such as nutrients and water (Machwitz et al., 2021).

Therefore, by observing the traits of numerous crops under various genotype-environment combinations, we can identify the most optimal phenotype that adapts to specific environments. This efficiency can show up in various aspects such as yield, fruit size or color, disease resistance, drought tolerance, adaptation to specific conditions like salinity, or any other desired trait. Globally, phenotyping is widely considered a key strategy for increasing crop productivity, necessitating the acquisition of high-throughput trait data (Jafarbiglu & Pourreza, 2022). In an agricultural context, remote sensing is the use of a device at a distance to observe vegetation and collect qualitative or quantitative data about it. The remote sensing platforms discussed in previous sections (Manned, UASs, and satellite) are a subset of phenotyping, so the methods used for those applications are also applicable to phenotyping. For example, Herrmann et al, (2020) used UAS mounted with a super spectral camera to assess maize yield and phenology, and Herr et al. (2023) used UAS imagery for phenotyping in cotton, maize, soybean, and wheat breeding.

2.4. Unmanned aerial vehicles (UAV) or Drones.

Drones can be defined as any unmanned aircraft that is operated with remote. Aircraft are divided into manned and unmanned aircraft; unmanned aircraft are then divided into flight models and unmanned aviation systems, or unmanned aerial systems (UAS). These divisions are based on operational purposes; if they are used for sports and leisure purposes, they are termed model aircraft; however, if they are used for other operational purposes, like commercial purposes, they are considered UAS (Mohsan et al., 2023). There is a clear distinction between a UAV and UAS. UASs re complete system that includes drones and other components, such as the control station on the ground. While UAVs are just unmanned aircraft or drones themselves (INSPIRED FLIGHTS, 2023). Drones are categorized into two, Fixed wing drones and Rotary wing drones.

2.4.1. Fixed wing drone.

Fixed-wing drones, or wing drones, are drones that are built like a model airplane. These are driven by an electric motor at the end of the fuselage and receive the lift required for flight due to the shape of the wings. Fixed-wing UAVs have gained popularity in military and defence applications due to their capacity to transport substantial payloads. Fixed wing UAVs are not suitable for stationary applications due to their inability to conduct close inspections. They utilise their wings to generate upward force and maintain flight. (Laghari et al., 2023) Fixed wing UAVs exclusively utilise energy to propel themselves in a particular direction while maintaining a stationary position in the air. The fixed-wing drone possesses the capacity to traverse long distances and conduct surveys of vast areas. A fixed-wing UAV can stay in the air for a maximum of 16 hours thanks to its use of a petrol engine rather than an electric one. (Rao, 2020)

Figure 2 . Example of fixed wing drone (Image source: Delair)

2.4.2. Rotary wing drone.

Engineers specifically designed a rotary-wing UAV to observe and assess ground conditions from an aerial perspective. Its primary functions include identifying and monitoring border areas, conducting surveillance on military assets, and other related tasks. (Pakrooh & Bohlooli, 2021). Rotary UAVs, commonly known as drones, have a restricted maximum speed and payload capacity compared to fixed-wing aircraft. They have the ability to remain in a fixed position in the sky. This type of UAV is capable of conducting a thorough and detailed inspection at close range. The selection of unmanned aerial vehicles (UAVs) is contingent upon their intended applications. (Mohsan et al., 2022)

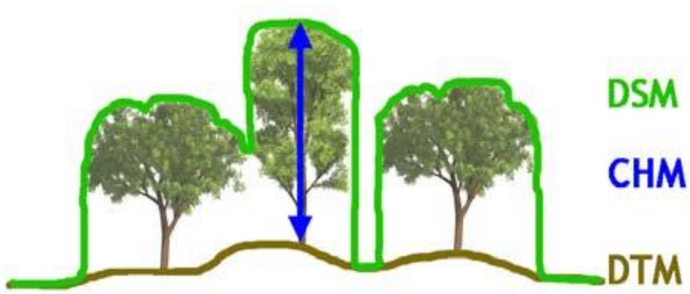
Figure 3. Example of rotary wing drone (Internet)

2.5. Plant height estimation.

Plant height data is required for breeding purposes so that any neighboring effects can be accounted for. Planting tall maize varieties next to shorter ones allows for the necessary correction or compensation of the yield disadvantage. As a result, tall plants or plots yield less, while low-growing plants or plots yield more (Kosola et al., 2023). The increasing adoption of remote sensing technology in agriculture is becoming more beneficial and simplifies work not only for farmers but also for agriculture researchers. In the agricultural sector, UAVs are also becoming increasingly useful tools. Researchers use UAVs for crop phenotyping, such as assessing plant height. The

UAVs are fitted with high-resolution cameras and specialized sensors such as RGB, multispectral, hyperspectral, thermal infrared imaging cameras, and light detection and ranging (LIDAR) systems that enable the gathering of detailed aerial images of plants, which will eventually allow a precise estimation of plant height. These types of sensors have proven to be effective devices for capturing phenotypic characteristics in multiple crop species (Shu et al., 2023)

UAVs are used to assess plant height through DTM (digital terrain models), DSM (digital surface models), and CHM (canopy height models). The first step involves obtaining the DTM, for which there are two methods available. The first method involves flying a drone when the ground is bare, meaning no plant growth is visible yet. The optimal time for this is after sowing. In the second method, the height data of the bare ground is created by the tractor's GPS during sowing. The GPS replaces the need for a drone. Then the determination of DSM is followed, where the drone is flown to determine the height of the terrain surface and the height of the plant. When DTM and DSM are available, the CHM is obtained by subtracting DTM from DSM, and the result is the height of the plant (Panagiotidis et al., 2017).See the figure 4 below.



CHM = DSM – DTM

Canopy Height Model

Digital Surface Model

Digital Terrain Model

Figure 4. plant height assessment (By. Perko 2010)

2.6. Plot quality assessment.

It's critical to accurately detect the emergence of seedlings and their growth in order to manage crops early. With the aid of an appropriate assessment of crop emergency, breeders can be able to select suitable crop genotypes of their interest, and farmers can make timely decisions about field management practices and maximise their production. The manual method of assessing crop emergence is likely to involve manual computations in the determination of the size and quantity of seedlings. This method is time-consuming, labour-intensive, unreliable, and inefficient since it can miss opportunities to visualise the spatial distribution and seedling consistency. There are a few aspects of crop emergence that are difficult to measure manually: the number of seedlings per unit area, the size of the seedlings, and the uniformity of their distribution. The uniformity of crop emergencies is very crucial since it helps to balance competition between plants for nutrients, water, and light (Karayel Davut et al, 2008). When compared to an average condition, the uniformity offers a more accurate representation of the distribution of crop seedlings within a plot. This, in turn, makes it possible to conduct a more precise evaluation of the quality of the material (Liu et al, 2023). A plot can be termed poor-quality due to poor emergency of seedlings and poor distribution or having a lot of bigger gaps between plants. This can be generated by several factors like poor seed quality, errors during sowing, bird damage, or the field's condition effects.

Studies have been conducted by a number of researchers in order to monitor and quantify the beginning of crop growth. The technology of remote sensing based on phenotyping technology delivers high-throughput assessment of crop emergence during early growth phase. Unmanned aerial vehicles (UAVs) fitted with a variety of sensors, such as RGB, are now becoming the most effective way to monitor plant growth and seedlings because of their capability to obtain high-resolution, real-time images, their efficiency in data collection, and their user-friendly operation. Researchers have demonstrated the ability to accurately detect phenology by employing established methodologies. For instance, Yang Q et al, (2020) used a fixed-wing drone to detect rice phenology based on UAV images, and Zhou M, (2023) used a UAV to detect wheat phenology.

2.7. Stand count assessment.

The stand count is an assessment of the population density of plants that have successfully emerged and established after sowing. It entails assessing the number of healthy and viable plants in a given area. The stand count initially provides information for assessing seed germination rates, evaluating planters' work efficiency, and guiding crop management decisions, such as thinning or replanting seeds to fill gaps. Stand count or plant population optimization in order to enhance productivity is important to both farmers and researchers. There is a direct correlation between the number of plants that are present in a given area of the field and the yield of the crop (Abuzar et al., 2011). Manually counting the plants is a time-consuming, laborious, and susceptible to mistakes method that is used in traditional methods of plant counting. This is in contrast to the ground-based sensing methods, which are restricted to more compact areas. It is possible to use computer vision algorithms in conjunction with high spatial resolution images obtained from unmanned aerial vehicles (UAV) in order to evaluate plant population. (Sankaran et al., 2017)

Remote sensing technology, through images captured by UAV can be efficiently used to determine plant stand count through different methods, such as traditional image processing, which can be employed to analyse images obtained by UAV in order to assess the plant population in the field. Traditional image processing entails a range of tasks, such as image enhancement, image restoration, and image analysis, that can be performed on digital computers to manipulate images. Other methods include machine learning and deep learning which were both reviewed by Pathak et al, (2022).

2.8. Weather requirement for drone flying.

Weather is a crucial factor for drone flights. A clear sky and low wind are the ideal weather. Fog, drizzle, or rain make it impossible to conduct a flight. Not only would this cause damage to the electric motor of the rotor blades, but it would also degrade the quality of the photos, making them unsuitable for evaluation. The result would be blurry images and data. Even a partly cloudy sky is not a good condition for a flight. Due to clouds and sunlight, the lighting conditions are constantly changing, and irregular shadow areas appear in the field. This, in turn, reduces the photo quality of the plots. Strong to very strong winds also pose a higher risk, as they can affect landing. When landing, it is important that there is a headwind on the approach. This is required for a smooth and damage-free landing, as the drone switches off the electric motor at a height of approx. 2 m above the ground and tilts the ailerons downwards in order to be able to land with the nose pointing upwards. Strong winds can hinder the landing process and cause damage to the aircraft. In windy conditions, it is important to ensure that the direction of flight of the drone is always at a 90° angle to the wind direction. This ensures that the drone maintains the same flight speed and takes as many photos as possible. If the flight direction is with the wind (tailwind), the drone flies faster in one direction and takes fewer photos (Gao et al., 2021).

A head wind causes the drone to fly slower when returning, allowing for more photo opportunities. The more wind there is, the more turbulent the UAV's flight behaviour is. Given the weather, the best conditions for a flight are a slightly windy, completely overcast, or cloudless sky. This means that the flight speed and the number of photos taken are largely constant. In addition, the drone's flight behaviour is relatively quiet due to the lack of wind. The cloudless or completely overcast sky ensures constant lighting conditions, resulting in high-quality photos and data (Wang et al., 2019).

2.9. Manual data collection.

Although technology plays an increasingly significant role in agriculture, manual data collection continues to be valuable for various farm operations. Farmers and agricultural researchers collect information firsthand during field visits regarding crop health, pest and disease presence, irrigation requirements, weather patterns, and various other field conditions. Subsequently, all the gathered information is meticulously documented for subsequent assessment and strategic decision-making. Visual observation is the primary technique for collecting data manually. Farmers and agricultural researchers conduct visual inspections of crops and meticulously record all pertinent information during field visits. The notebook or logbook may contain dedicated sections for documenting plant health, pest presence, irrigation needs, weather conditions, and other relevant field activities. Typically, individuals write notes by hand in notebooks or digitally record them on tablets or phones.

Activities like crop health and growth monitoring through the manual method, which involve the assessment of nutrient content in plant tissues to determine crop health and nutritional status, can be done manually by observing the colour of the leaves of certain crops. For example, if there is a nitrogen (N) deficiency in corn, the plants will turn pale, yellowish green with spindly stalks starting from older leaves to lower leaves and spreading throughout the plant if not addressed (Sawyer, n.d., 2004). In agricultural research, for example, in plant breeding, quantitative genetic data provides an understanding of how quantitative traits change over the generations of crossing and selection (Beavis et al., 2023), e.g. The height of the plant is one of the quantitative data points that can be obtained through manual method by measuring the height of the plant using a tape measure. You can manually collect a variety of other data on the farm, including tracking pest and disease presence, monitoring plant growth and development, identifying weed encroachment, and managing irrigation.

Manual data collection gives simplicity and ease of application; it is available in various ways, for instance, during field scouting. However, manual data collection has disadvantages, like employing human errors that lead to inefficiency in the collected data. It is also a time-consuming method and requires a large workforce when dealing with large areas. These shortcomings demand the need for more efficient and accurate data collection methods, especially where the context of precision and reliability is vast.

CHAPTER THREE.

3. MATERIAL AND METHOD.

We timed the necessary times and individual work steps for the two assessment variants separately in the test field using a stopwatch on a mobile phone. This guarantees the recording of the documented times under real-world scenarios. Therefore, we have halted the data transfer and processing times on the station's office computer. The study took place between 10th July to 27th October 2023 during my internship period at Limagrain GmbH.

3.1. Location.

We conducted the study at Pocking Breeding Station. In 1990, Limagrain GmbH established the Pocking breeding station. At the time, there were four full-time employees working on 10,000 plots. By 2003, researchers had conducted experiments on approximately 30,000 plots, established a breeding garden with 4,300 plots, and propagated seeds on 3,000 plots at various locations in Bavaria and Austria. They created and maintained experimental areas in Bavaria, East Germany, the Czech Republic, and Poland from 2003 to 2013. With a total of 132,050 plots, 2013 was the year with the most plots to date. From then on, the Pocking breeding station only looked after the experimental areas in Bavaria and East Germany. The reason for this was the establishment of a station in Poland, which took over the test areas in Poland and the Czech Republic. Up until 2020, the station in Pocking created 21,600 plots for observation and 6,700 as breeding gardens, out of a total of 121,350 plots. There are currently 13.75 full-time employees (40 hours per week) working at the station in Pocking. Within 30 years, the station's location grew from four to 13.75 employees and from 10,000 to 121,350 plots.

There are three teams at the station: two breeding groups, one group breeding only grain maize, and the second breeding team breeding both grain and silage maize. The technical experimentation team (PX), which is responsible for supervising the silo and grain maize experiments, is the third team. This includes field planning, sowing preparation and implementation, scoring plots, harvesting trials, and validating the sowing, scoring, and harvest data. In total, the PX team looks after 84,000 plots on 17 experimental fields at seven experimental locations, which are in Bavaria, Saxony-Anhalt, and Brandenburg.

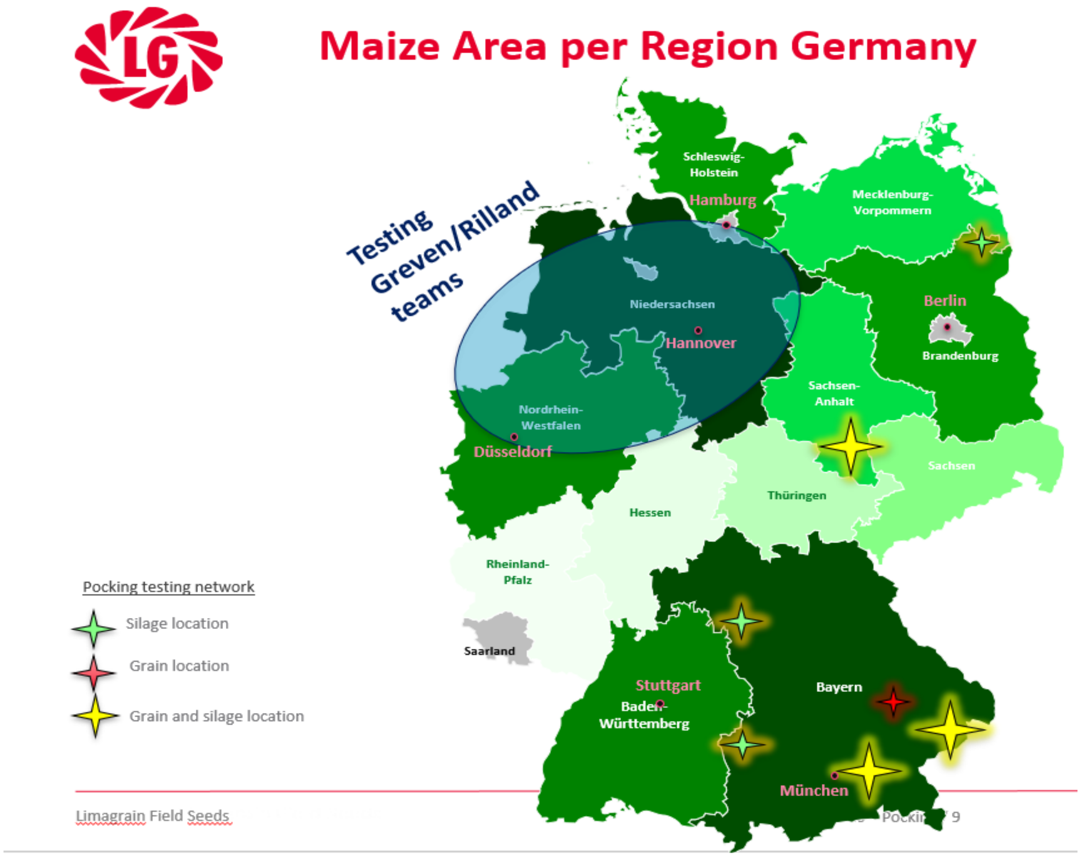


Figure 5. A map showing different testing fields locations in Germany (by: Limagrain GmbH)

3.2. Experiment setup.

The experiment was conducted in three trial fields managed by Pocking breeding station, we named the fields Location **A, B**, and **C**.

Location **A** is located in Pocking city in the south west of Passau district, Germany, with coordinates (N 48° 24', E 13° 19'). This location contains 5200 plots, and each plot measures 1.5 m wide and 6 m long (1.5m x 6m).

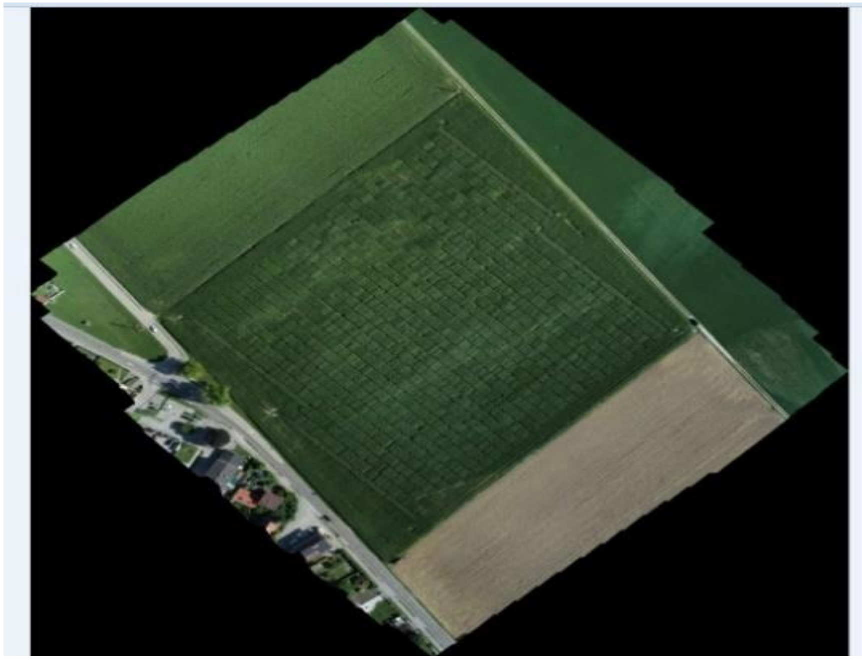


Figure 6. A picture showing Location A with 5200 plots. (By CAKAJ Hajirullah)

Location **B** is located in Linz city in Austria, with coordinates (48º18'21"N, 14º17'11"E), has **11,000** plots, each plot measuring 1.5 m wide and 6 m long (1.5m x 6m).

Figure 7. A picture showing location B with 11,00 plots. (By CAKAJ Hajirullah)

Location **C** Liepzing in Saxony state in Germany with coordinates (51^{o}20' 24" N, 12 ^{o}22'30" E) comprising of 15,000 plots and each plot measuring 1.5 m wide and 6 m long.

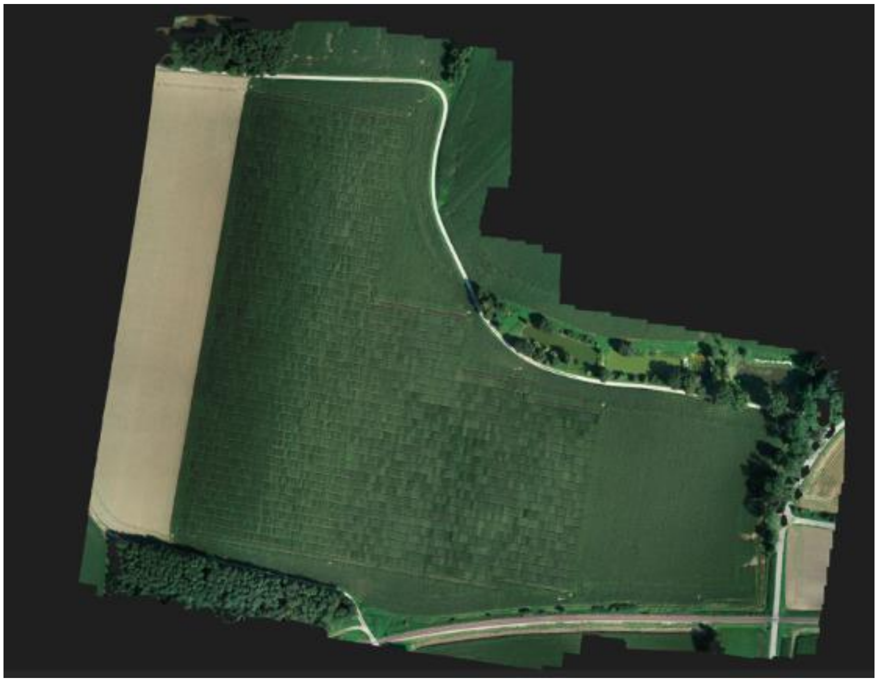


Figure 8. Location C with 15,000 plots. (By CAKAJ Hajirullah).

3.3. Treatments.

3.3.1. Manual method.

Manpower is required for the manual method of data collection. Company employees, students, and other seasonal workers were the sources of manpower. Students and seasonal workers were trained on how to use electronic hand device, an electronic device that allows for the digital recording of credited data. The time spent on manual assessments was meticulously recorded in this study. The recorded time includes short breaks for accurate measurements and data collection. After assessing all plots, we exported the data to a computer, checking for any transposed numbers or incorrect entries to ensure accuracy. Plant height was done by two people working together, one with measuring tool another with dolphin, for the plot quality and stand correlation, the manual method of visual observation was involved. We were going through the fields and recording the observations according to the required criteria.

3.3.2. Drone (UAVs) method.

A drone from the manufacturer Delair with the model's name, UX 11 AG, was used to collect data. Note that we did not include the time required to retrieve the drone from its landing site and transport it back to the car. This duration can vary depending on the surface and distance, taking longer or shorter as required. We did not factor this aspect into the calculations, as it usually takes only a few minutes. We flew the fully configured drone into the field to collect information at three different locations. A trained trial technician operated the drone. Every time we flew, we checked the weather to see if it was suitable.

Due to wind direction, the drone flew the length of a long, narrow field, which is significantly faster than flying across its width. Furthermore, the amount of overlap significantly influences the flight duration. Increased overlap means more photos of the area are taken, resulting in denser flight paths. As a result, the drone covers the area more frequently, which leads to longer flight times. Ideally, trajectories should overlap significantly. However, in large fields, excessive overlap can significantly increase flight duration, necessitating adjustments to preserve battery life.

3.4. Parameters.

3.4.1. Plant height.

Manually, plant height was measured within the two central rows of the four-row plots, we excluded the two rows on the outer edges, whose primary function is to mitigate any edge effects felt by the inner rows. Two people carried out this assessment using the manual method. Using a 5-meter-long, extendable measuring rod, person number one entered the rows of plots to take measurements. We used two plants from each of the two core rows in the middle of the plot for the measurements. The person with the measuring rod measured the height of each plant's topmost leaf base. The second person stood on the path between the plots with dolphin (a hand device for data entry), then calculate the average from the measured height measurements and entered it into the hand electronic device.

3.4.2. Plot quality.

Plot quality evaluates the growth of plants after sowing and identifies any missing or damaged plants within the plots. After sidling emergence, damage evaluation is done, and then the affected plots are recorded. The damage observed in the trial field is caused by a variety of factors, including poor seed quality, sowing inaccuracies, bird damage, and field-specific influences. This data is extremely useful to breeders because it alerts them to any unusual plots, which they can then exclude during the selection process. Plot quality also known as s damage ratting, denoted by a code 0449 code in Dolphin.

To grade the plots, they are evaluated and classified using various criteria. Limagarain GmbH using a scale of three grade points to grade plot quality. We evaluated each plot using specific criteria to decide whether to keep it or eliminate it. The worst condition given grade 1, will eventually be elimination. If the plot becomes unusable due to excessive or significant gaps between rows, we may assign this grade. We also consider plots with a grade of 5 as inadequate, having average condition, can be reassess their status at harvest to determine if conditions have improved. Although gaps may exist, it is possible that the plants will fill them in or compensate as they grow. Grade 9 is excellent, which has very few gaps and plant loss, which indicates optimal plot quality. This evaluation criteria are the same by manual method and UAV.

The table below shows the evaluation criteria of plot quality.

Table 1. Evaluation criteria and grades of the plot quality.

Evaluation criteria	**1**	**5**	**9**
Number of plants/plots %	<70%	<70% - 80%	< 80% - 100%
Number of missing plants/plots **%**	>30%	<30%->20%	< 20%

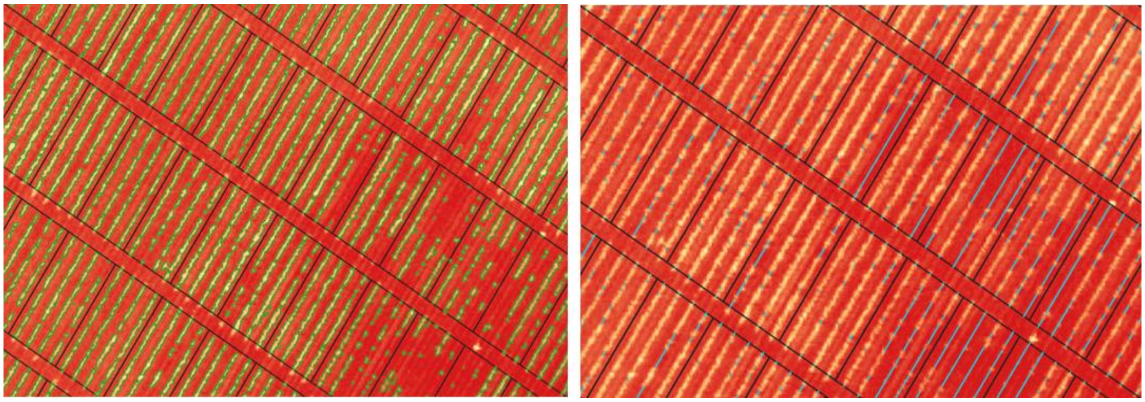


Figure 9 Images show patchy plots, after plot quality assessment performed by UAV (by:Limagrain 2020a)

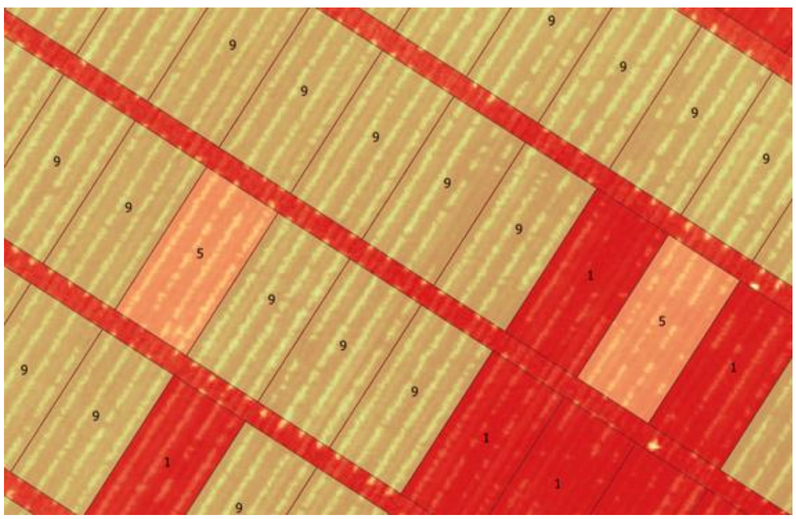


Figure 10. Image shows graded plots after plot assessment by UAV (By:Limagrain 2020b)

3.4.3. Stand count.

the assessment of the population density of plants that have emerged and established in a field after planting, it involves counting the number of healthy and viable plants per unit area. Maize field counts are crucial for determining the planting process; they give details of seed germination rates, evaluate planting practices, and make crop management decisions such as thinning or replanting of seeds. The stand count was assessed manually, with one person going within the plots to determine plant population density in 1 hour time, aim was to determine how many plots can be assessed by a single person within in an hour. All drone flight assessments were performed by expert from Limagrain.

CHAPTER FOUR

4. RESULTS AND DISCUSSION.

4.1. Location A.

4.1.1. Plant height results.

The assessment of plant height in Location A. The manual method was done by a pair of people working together, and the drone by one person. The drone flew at speeds between 30 and 35 km/h 100m above ground level. Two flights were involved in measuring plant height, first at bare soil for point zero and second at canopy flight.

Table 2. *Show the results on plant height at Location A.*

	Manual		**Drone bare soil**	**Drone canopy**
Total no. of plots	5200	Total nr. of plots	5200	5200
No. plots/1hr	75	Flight hours	0.5	0.5
office work hrs	0.5	office work hrs	1	2.5
Total no. of hrs	**69.8**	**Total nr. of hrs**		**4.5**

Chart below (figure 10) shows comparison between manual and UAV method in assessing plant height at location A.

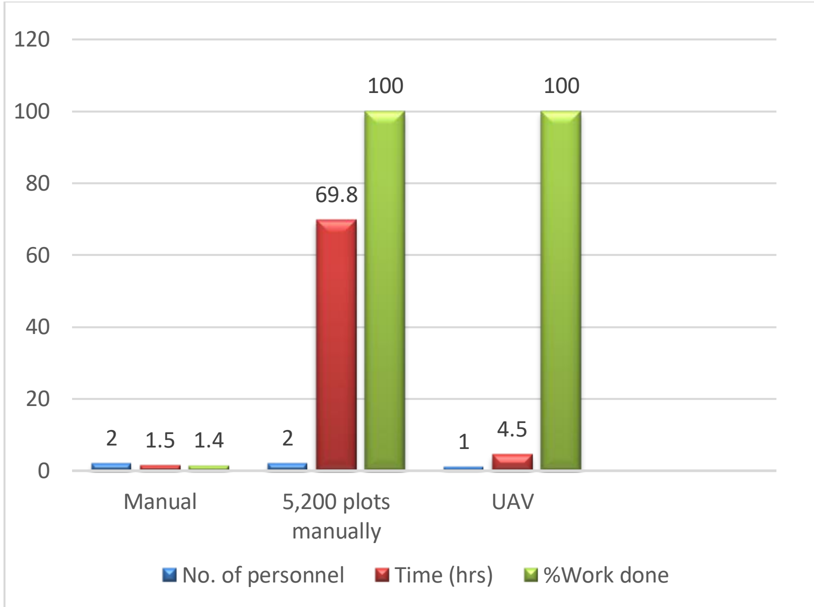


Figure 11. Comparison between manual and UAV in assessing plant height at location A.

The chat above demonstrates that, in the first triplets' bars, a team of two people working together spent 1.5 hours doing both field work and office work to score 75 plots, which represents 1.4% of the total work. Thus, it would take approximately 69.8 hours to complete 100% of the work (which comprises 5200 plots) by the manual method, as shown in the second triplet bar. Furthermore, the manual assessment of plant height would require the participation of 70 pairs of people, for a total of 140 individuals to assess plant height in 1.5 hours, which means more people will be needed to accomplish the work. Using a drone, a single person would need 4.5 hours to assess plant height in 5200 plots, which represents 100% of the work as shown in the third triple. The manual method will require a huge amount of manpower to finish the work on time.

4.1.2. Plot quality results

One person manually assessed the plot quality in Location A, while a drone with one operator conducted the assessment. The drone was flown at a speed between 10 and 15 KM/H and 50m above ground level. The larger number of images required more time during office hours for image uploading and processing. Table 3 below. shows the results of the plot quality assessment based on the recorded time spent scoring using the two methods, manually and drone.

Table 3. *Results in assessment of plot quality location A.*

	Manual		Drone
Total nr. Of plots	5200	Total nr. of plots	5200
No. of plots/1hr	300	Flight hours	1
office work hrs	0.5	office work hrs	2.5
Total nr. of hrs	**17.8**	**Total nr. of hrs**	**3.5**

Chart below shows comparison between manual method and UAV assessing plot quality at location A.

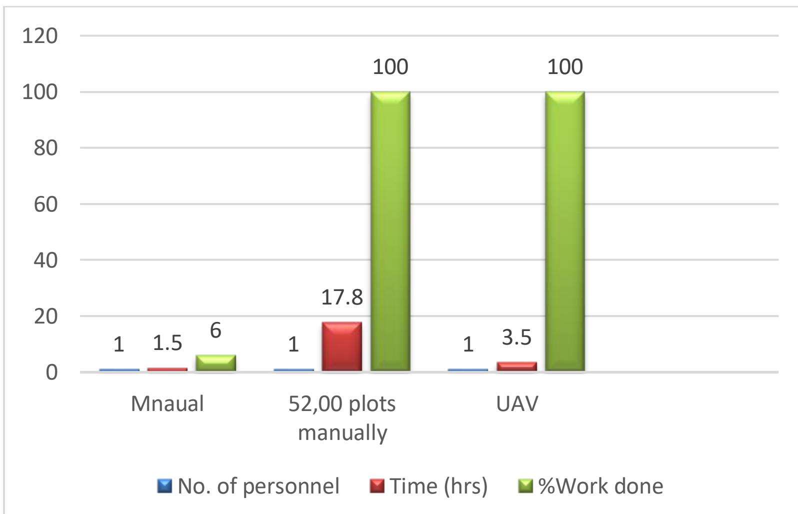


Figure 12. Comparison between manual and UAV methods in assessing plot quality at location A.

The graph above shows that a single person spent 1.5 hours scoring 300 plots, which equates to 6% of the total work as shown in the first triplet's bars. Therefore, in the second triplet's it demonstrates that, in order to complete 100% of the work, which includes 5200 plots, 17.8 hours of work would be required, encompassing both field and office work hours. Furthermore, manually scoring 5200 plots in a single day will necessitate a significant workforce; approximately 18 individuals are required to score 5200 plots in 1 hour. Using a drone, a single person in operation was able to complete 100% of the work (which comprises 5200 plots) in 3.5 hours as shown in the third triplet's bars, including office working hours for image uploading and processing.

4.1.3. Stand count results.

The experiment of assessing the stand count manually was done by one person, and the drone was also operated by one person. The drone was flown at a speed between 4 and 6 km/h, and the height was 20m above ground level. We recorded the number of plots scored and the time taken. Table 4. below shows the results on stand count assessment manually and by drone.

Table 4. *Shows the results on stand count assessment manually and by drone.*

	Manual		**Drone**
Total no. of plots	5200	Total no. of plots	5200
No. of plots/1hrs	100	Flight hours	2.5
office work hrs	0.5	office work hours	3
Total nr. of hrs	**52.5**	**Total nr. of hrs**	**5.5**

The chart below shows the comparison between manual and UAV method in assessing stand count at location A.

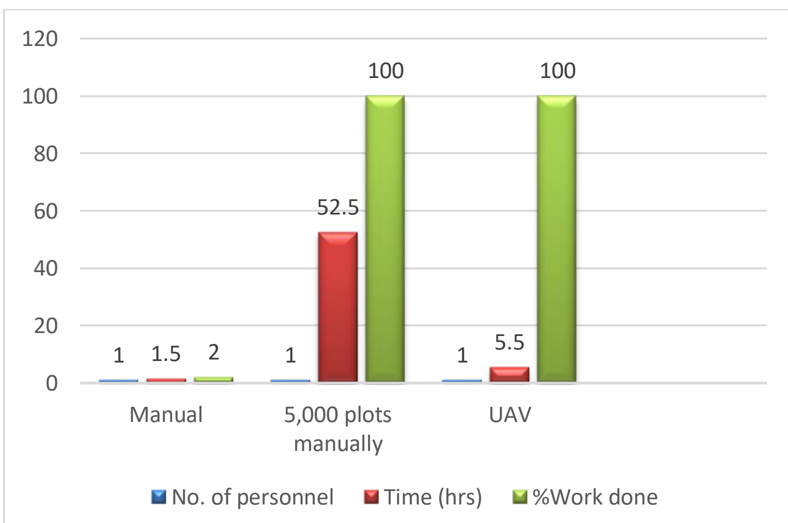


Figure 13. Comparison between manual and UAV method in assessing stand count at location A.

The graph above shows that scoring the maize stand count manually in the first triplet's bars, a single person spent 1.5 hours to score 100 plots, which represents 2% of the total work; therefore, to complete the work in 100%, or 5200 plots, it will take 52.5 hours as shown in the second triplet's bars. Furthermore, if you intend to reduce working hours, manually scoring would require a large amount of manpower. Additionally, increasing the number of people is necessary to complete the work at 100%. According to the chart, 53 people will be able to score 5200 plots in an hour. The graph shows that one person, using a drone, could score 5200 plots in 5.5 hours, representing 100% of the total work done in assessing the stand count in Location A as shown in the third triplet's bars.

4.2. Location B

Location B consists of 11,000 plots, each measuring 1.5m wide and 6 m long (1.5m x 6m).

4.2.1. Plant height results.

Two people working together manually assessed the plant height, and one operator used a UAV. We flew the drone twice: once on bare soil to establish point zero, and again during canopy flight. We flew the drone at a speed of 30 to 35 km/h and 100 m above ground level. We recorded the number of plots scored and the time taken. The table 5 below shows the results on assessing plant heigh manually and by UAV in 11,000 plots.

Table 5. *Shows the results on assessing plant heigh location B.*

	Plant height			
	Manual		**Drone bare soil**	**Drone canopy**
Total nr. of plots	11,000	Total nr. of plots	11,000	11,000
nr. of plots/1hrs	75	Flight hours	1.5	1.5
office work hrs	0.5	office work hrs	1	3
Total nr. of hrs	**147.2**	**Total nr. of hrs**		**7**

The graph below shows comparison between manual and UAV methods in assessing maize plant height at location B.

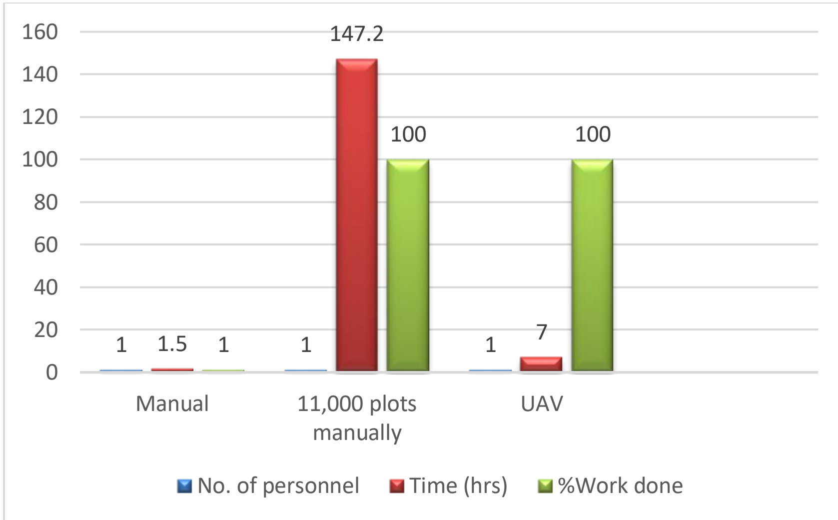


Figure 14. Comparison between manual and UAV methods in assessing plant height at location B.

The graph shows that in assessment of plant height, which involves two people working together, took 1.5 hours to assess plant height in 75 plots, or 1% of the total task as shown from the first three bars. However, the graph in the second triplet's bars, also shows that completing the entire task, which includes 11000 plots, would require 147.2 hours of work. As a result, assessing maize plant height manually requires a large amount of manpower; approximately 147 pairs of people (294 people) will be needed to finish the task in 1.5 hours. While using drone, a 1 person could score 11000 plots in 7 hours, including office working hours for image uploading and processing; hence, by using a UAV, a single person could complete 100% of the work, as shown in the graph, in less time compared to the manual method with two people working together.

4.2.2. Plot quality results.

Assessment of plot quality was done manually by a single person in one hour to determine how many plots could be scored, and by drone, one person was involved in scoring. The drone was flown at a speed between 11 and 15 km/h and 50m above ground level. Table 13 displays the time required for scoring and the number of plots recorded. Table below shows the results on plot quality assessment by manual and UAV methods in 11,000 plots. Table 6 below shows the results on plot quality assessment by manual and UAV methods at location B.

Table 6. Results on plot quality assessment location B.

	Manual		**Drone**
Total nr. of plots	11,000	Total nr. of plots	11,000
nr. of plots/hrs	300	Flight hours	2.5
office work hrs	0.5	office work hrs	3
Total nr. of hrs	**37.2**	**Total nr. of hrs**	**5.5**

The graph below shows comparison between manual and UAV methods in assessing plot quality at location B.

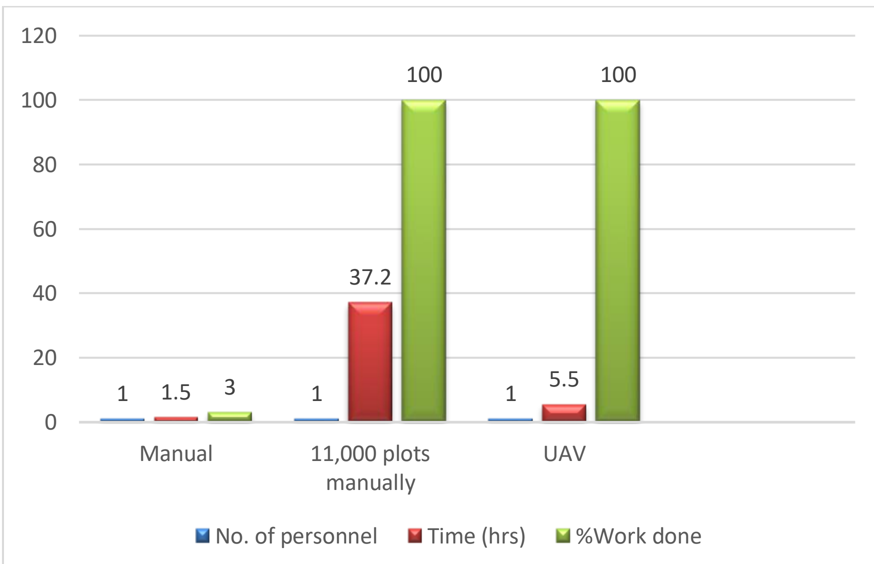


Figure 15. Comparison between manual and UAV methods in assessing plot quality at location B.

According to the graph above, the first triplet's bars show that, one person could spend 1.5 hours (in the field and office) to manually score plot quality on 300 plots, which represents 3% of the total work. Therefore, to complete 100% of the task, 37.2 hours of work (both in the field and office) would be required to score 11,000 plots as shown in the second triplet, which is equivalent to 100% of the work. Furthermore, manual assessment would require a large number of people to work; for example, it would take 37 people to score 11,000 plots in an hour. Using UAV, a single person could complete 100% of the work to score 11,000 plots in 5.5 hours, as demonstrated in the graph above in the third triplet bars. The use of UAV means a reduction in manpower workload.

4.2.3. Stand count results.

In the assessment of plot quality, one individual was involved, both manually and by drone. The speed of the drone was between 4 and 6 km/h, and the height was 20 m above ground level. The time and number of plots assessed were recorded. Table 7 below shows the results on assessment of stand count by the two methods, manually and UAV in a field of 11,000 plots at location B.

Table 7. *Results on assessment of stand count at location B.*

Stand Count			
	Manual		**Drone**
Total nr. of plots	11,000	Total nr. of plots	11,000
nr. of plots/1hrs	100	Flight hours	6
office work hrs	0.5	office work hrs	5
Total nr. of hrs	**110.5**	**Total nr. of hrs**	**11**

The Graph shows the comparison between manual method and UAV in assessing stand count in Location B.

Figure 16. Comparison between manual and UAV in assessing stand count in Location B.

The graph above reveals that, by the manual method of assessment of stand count in the first triplet's, one person spent 1.5 hours to score 100 plots, representing approximately 1% of the total work required. Furthermore, to complete the work at 100%, assessing 11,000 plots manually will take 110.5 hours as shown in the second triplet's bars. To complete the work manually, a significant number of people will be required. For example, 110 individuals will be required to score 11000 plots within 1.5 hours. By using a drone, a single person spent 11 hours working both in the field and in the office to complete the work at 100% in the assessment of the stand count in 11000 plots.

4.3. Location C.

Location C consists of 15,000 plots, each plot measuring 1.5m wide and 6 m long (1.5m x 6m).

4.3.1. Plant height results.

Two people worked together to assess plant height manually, while one operator used a UAV. We flew the drone twice: once on bare soil at point zero and again during canopy flight. The drone was flown at 30 to 35 km per hour and 100 m above ground level. We recorded the time and the number of plots scored. Table 8 below shows the results on assessment plant height by the two methods, manually and UAV in a Location C.

Table 8. Results on assessment of plant height at Location C.

	Plant height			
	Manual		**Drone bare soil**	**Drone canopy**
Total nr. of plots	15,000	Total nr. of plots	15,000	15,000
Nr. of plots/1hrs	75	Flight hours	2	2
office work hrs	0.5	office work hrs	1	4
Total nr. of hrs	**200.5**	**Total nr. of hrs**		**9**

The graph below (figure 9) shows the comparison between manual method and UAV in assessing plant height in Location C.

Figure 9. Comparison between manual and UAV in assessing plant height at Location C.

For the assessment of plant height, two people spent 1.5 hours assessing 75 plots, which represents 0.5% of the total work. It will take 200.5 hours to complete the entire task at 100%, which is assessing a total of 15,000 plots. Attempting to reduce the working hours from 201.5 hours would require the addition of more personnel, for it requires 201 pairs of people (402 individuals) to score 15,000 plots in 1 hour. Using the aerial method with a drone, a single person spent 9 hours working both in the field and in the office to score 15,000 plots, representing 100% of the work completed, as shown in Figure 9. Using a UAV means working less but covering a huge work area.

4.3.2. Plot quality results.

In the assessment of plot quality, one person was involved to score manually, and another person worked with a drone. The drone was flown at speeds between 11 and 15 km/h and 50 m above ground level. The time and number of plots scored were recorded as shown below in table 9.

Table 9. *Results on assessment of plant height at Location C.*

Plot quality			
	Manual		Drone
Total nr. of plots	15,000	Total nr. of plots	15,000
Nr. of plots/hrs	300	Flight hours	3
office work hrs	0.5	office work hrs	3
Total nr. of hrs	**50.5**	**Total nr. of hrs**	**6**

The Graph below shows the comparison between manual method and UAV in assessing plot quality in Location C with 15,000 plots.

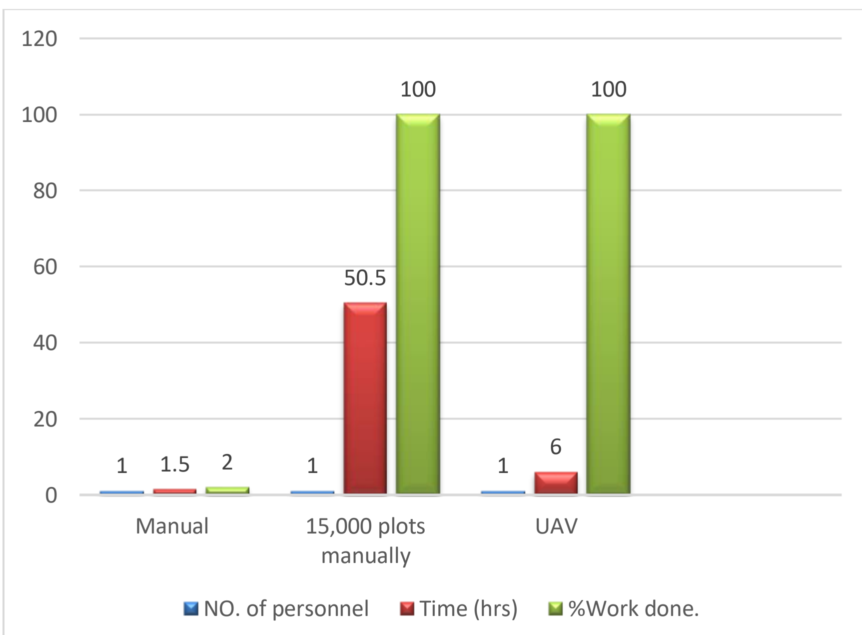


Figure 17. comparison between manual and UAV in assessing plot quality in Location C.

The results show that a single individual, assessing plot quality manually, spent 1.5 hours scoring 300 plots, or 2% of the total work. The total work comprises 15,000 plots, indicating that a single person would need to work 50.5 hours (field and office work hours) to assess plot quality at 100% in Location C. This implies that 51 people would be required to complete the entire task in 1.5 hours. Using a drone, a single person could spend 6 hours working both in the field and in the office, resulting in the completion of 15,000 plots, representing 100% of the work, as demonstrated in the graph above.

4.3.3. Stand count results.

In the assessment of plot quality, one individual was involved, both manually and by drone. The speed of the drone was between 4 and 6 km/h, and the height was 20 m above ground level. The time and number of plots assessed were recorded. More time was needed during office hours for image uploading and processing. Table 10 below Shows the results on assessment of stand count/plant counting by the two methods, manually and UAV in a Location C.

Table 10. *Results on assessment of stand count at Location C.*

Stand Count			
	Manual		**Drone**
Total nr. of plots	15,000	Total nr. of plots	15,000
Nr. of plots/1hrs	100	Flight hours	9
office work hrs	0.5	office work hrs	6
Total nr. of hrs	**150.5**	**Total nr. of hrs**	**15**

The Graph below shows the comparison between manual method and UAV in assessing stand count/plant counting in Location C with 15,000 plots.

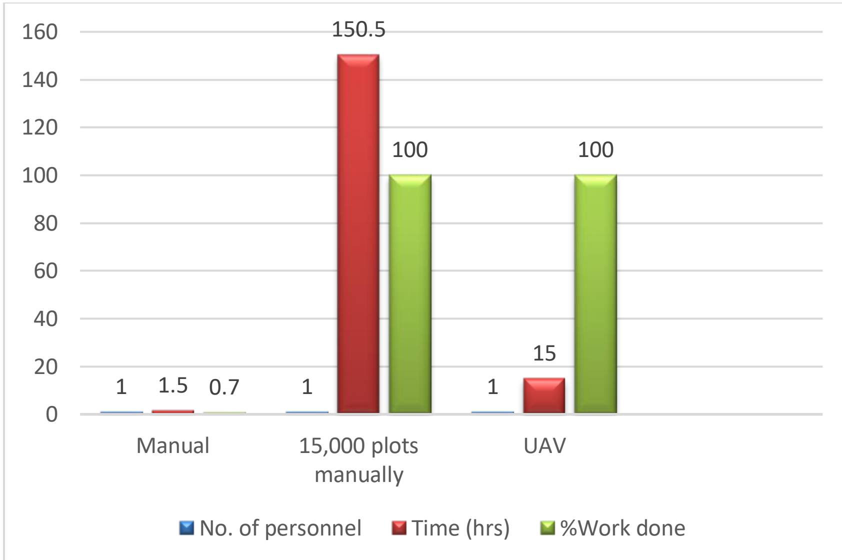


Figure 18. Comparison between manual and UAV in assessing stand count at Location C.

In the assessment of stand count in Location C, manual method, 1 person spent 1.5 hours to scored 100 plots, which is 0.7% of the total work see the first three bars from graph abo. Hence, to be able to score 15,000 plots, which is 100% of the work, will require 150.5 hours of working both in the field and office as shown in the second triplet's bars. Additionally, to score 15,000 plots in a single day demands for more work force. Because it will take 151 people to complete the task in 1.5 hours. While using a UAV, in the third triplet show that only a single person will work 15 hours of both field work and office work of image uploading and processing to score 15,000 plots, which is 100% of the work.

4.4. A brief general discussion.

From the previously discussed locations A, B, and C, it shows that manual data collection is a time-consuming method and requires a huge amount of manpower, although it seems to be a cheap and fast method if the size of the area or field is small. Employing the manual method for data collection in large fields will require a large number of people. A large number of people is cost-effective, but stable management is required to ensure work efficiency. Reducing the number of people may result in the need for many days of work depending on the farms or company's working hours per day, which could impact uniformity. Employing UAVs for data collection may necessitate fewer working hours and a reduced manpower requirement, but it will yield excellent results. This is similar to what Nhamo et al. (2018) found: they used manual and UAV methods for collecting information in their agricultural research. The manual method turned out to require more working days compared to the UAV method; see the figure below.

Table 11. *Comparison between manual and UAV method in ground truthing* (Nhamo et al., 2018)

Fieldwork Type	Days Spent in the Field	No. of Points	Frequency (Points/Day)	No. of Equipment	Equipment Cost (US$)	No. of Personnel
Manual	25	137	5.5	2	885	2
UAV	7	74	10.6	1	1900	1

5. CONCLUSION.

This study compares two methods of data collection: aerial, which uses UAVs or drones, and manual, which requires human effort. We collected data in three distinct maize fields, identified as Locations A, B, and C. The collected data included plant height, plot quality, and stand count. The goal was to determine which method would take less time and manpower while producing significant work output, expressed as a percentage. The results show that the manual method is more labor-intensive and time-consuming than the UAV method, which requires less manpower and time while covering large areas quickly.

Across all three locations, manual assessment method, it became clear that completing the task at 100% would necessitate significant working hours. Attempting to reduce these hours would necessitate hiring more people, resulting in a high demand for labor. For example, in Location C, which has 15,000 plots measuring 1.5m wide by 6m long, a pair of workers could only assess 75 plots per hour, or 0.5% of the total workload. To complete the entire task manually at 100%, it would take 201.5 hours for a pair to assess 15,000 plots, implying that 201 pairs of workers (402 individuals) would be required to complete the task within an hour, whereas a drone would only require one person to complete the task in 9 hours. This is consistent with other assessments from all three locations. Using a UAV, a single person can complete a large amount of work in a short period of time. For example, when assessing plot quality at location C, a single individual using a drone could score 15000 plots in 6 hours, whereas a single individual manually would take 50.5 hours. The use of UAVs demonstrates the reduction of farm work load in advance because it requires less manpower and takes less time to complete the task. To be able to combat the challenges of the future derived from increasing population and increasing food demand, it is inevitable to use remote sensing technology since it delivers precise and on-time data and covers huge areas with less manpower, which in turn delivers high production.

SUMMARY.

Title: Remote sensing in agriculture: Comparison between manual and UAV methods in data collection in maize trial fields.

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Technological advancements and rising global food demand due to population growth are driving the increasing use of remote sensing technology in agriculture. There is an urgent need for sophisticated technology capable of efficiently completing large-scale tasks within tight deadlines. Unmanned Aerial Vehicles (UAVs), which act as a remote sensing platform, are becoming increasingly popular in agricultural applications. They enable the collection of diverse field data without direct physical contact with the subject, and they play an important role in precision agriculture (PA) by providing precise information required for management decisions. However, despite its time-consuming nature and lower accuracy, manual data collection remains the most traditional and cost-effective method in agriculture.

This study is based on comparing these two data collection methods: the aerial method, which involves using a UAV or drone, and the manual method, where people are involved in data collection. The study conducted data collection in three distinct maize fields, identified as Locations A, B, and C. We conducted three types of assessments: (1) Plant height, manually required two people working together: one person holding the extendable measuring rod to determine the plant's height, and the second person recording the measured height using a mobile-like device named Dolphin, which transformed data directly to the station. (2) Plot quality assesses the growth of plants after sowing and identifies any missing or damaged plants in the plots, and was manually completed by a single person, who then recorded the data. Lastly, (3) stand count, refers to the process of assessing the density of plants that have emerged and established in a field following planting. We count the number of healthy and viable plants per unit area. One person, armed with a dolphin, also conducted the assessment. One person, a trained trial technician from the company, operated the UAV in all three assessments.

The goal was to determine which method, out of the two, could complete a significant amount of work in a short period of time and with minimal manpower, as measured by the percentage of work completed. The findings revealed significant differences in plant height assessments between manual and UAV methods across all sites. The manual method necessitates adding a large workforce to complete the task effectively. For instance, in Location C, which has 15,000 plots measuring 1.5m wide by 6m long, a pair of workers could only assess 75 plots per hour, which represents 0.5% of the total workload. To complete the entire task manually at 100%, it would take 201.5 hours for a pair to assess 15,000 plots, implying that 201 pairs of workers (402 individuals) would be required to complete the task within an hour. In contrast, using a drone, a single person spent 9 hours in both the field and the office assessing 15,000 plots, resulting in 100% completion of the work, as shown in Figure 9. Locations B and C also show that employing a UAV result in fewer working hours and significant work completion.

In the assessment of plot quality, there was also a huge difference. In Location A, a single individual could score 300 plots in 1 hour, representing 6% of the total work required, as depicted in the graph. Consequently, completing 100% of the work, which includes 5200 plots, would necessitate 18 hours of work, encompassing both field and office hours. Additionally, manually scoring 5200 plots in a single day will necessitate a significant workforce; the graph indicates that 17 individuals are required to score 5200 plots in 1 hour. Using a drone, a single person in operation will be able to complete 100% of the work (which comprises 5200 plots) in 3.5 hours, including office working hours for image uploading and processing. This is similar to locations B and C. Lastly, the stand count assessment at location B revealed that a single person, using the manual method, would need 1.5 hours to score 100 plots, representing approximately 1% of the total work required, as depicted in the graph. Furthermore, to complete the work at 100%, assessing 11,000 plots manually will take 110.5 hours. To complete the work in a single day, a significant number of people will be required. For instance, the graph indicates that 110 people are required to score 11,000 plots in an hour. Using a drone, a single person will spend 11 hours working both in the field and in the office to complete the work at 100%. in the assessment of the stand count in 11,000 plots; this was also similar in Locations A and C.

In general, the manual method takes longer and produces less work; therefore, reducing working hours will necessitate a large amount of manpower. A high number of people will actually affect the efficiency of work if the management isn’t strong. While the UAV means a reduction in farm work load, within a few hours it can perform great work and more efficiently. Compared to manual methods, UAVs require fewer personnel.

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LIST OF TABLES.

LIST OF FIGURES

APPENDICES.

Figure 19. Pictures of drone during takeoff and landing (Photo by Peter Mloha)

Figure 20. From the picture (Peter Mloha) holding dolphin a digital hand device we used to collect data manually (Photo taken by A.Shemahonge)

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