A Study to Determine Yield for Crop Insurance using Precision Agriculture on an Aerial Platform

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By

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Agniswar Mookherjee.

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List of Abbreviations

BGNIR	Blue-Green-Near Infrared
CSM	Crop Surface Model
DSM	Digital Surface Model
DTM	Digital Terrain Model
ENDVI	Enhanced Normalised Difference Vegetation Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GNDVI	Green Normalised Difference Vegetation Index
GCP	Ground Control Points
GIS	Geographic Information System
GVI	Green Vegetation Index
LAI	Leaf Area Index
NDVI	Normalised Difference Vegetation Index
PA	Precision Agriculture
RGB	Red-Green-Blue
RMSE	Root Mean Square Error
RS	Remote Sensing
UAV	Unmanned Aerial Vehicle

Preface

“Crop Statistics are important for planning, policy making and timely interventions to address food security” – Elijah Cheruiyot.

The agricultural sector is ‘ploughed up’. Unmanned aerial systems (UAV) have been making important contributions to the technological revolution in agriculture. Equipped with several sensors and microcontrollers, NIR and multispectral cameras, GPS receivers and many more, they support farmers in the efficient use of plant protection products, providing important data on the type of soil and protecting crops from diseases. Accurate and timely estimates or prediction of crop production in regional scale is critical for many applications such as food security warning system, agricultural lands management, crop insurance, food trade policy and carbon cycle research.

Reliable estimates of crop yields are important planning tools (Doraiswamy et al. 2003). The earlier in a growing season that an accurate yield prediction can be made, the more useful the analysis will be.

1. Introduction

1.1 Background

Crop yield monitoring and estimation have proved to be of vital importance for planning and for taking various policy decisions. The early prediction or forecasting of crop yield well before harvest is crucial especially in regions characterised by climatic uncertainties. This enables planners and policy makers to determine the amount of crop insurance to be paid to farmers in case of famine or a natural calamity. It also enables decision makers to predict how much to import in case of shortfalls or export in case of surplus.

Precision agriculture (PA) is the application of geospatial techniques and remote sensors to identify variations in the field and to deal with them using alternative strategies. Precision agriculture is a way of addressing production variability and optimising management decisions. Precision agriculture accounts for production variability and uncertainties, optimises resource use and protects the environment (Gebbers and Adamchuk, 2010; Mulla, 2013).By definition, a complete precision agriculture system consists of four aspects:

- Field variability sensing and information extraction,
- Decision making,
- Precision field control, and
- Operation and result assessment (Yao et al., 2011).

Precision agriculture adapts management practices within an agricultural field, according to variability in site conditions (Seelan et al., 2003).

Variability is well known to exist within many of agricultural fields. The causes of variability of crop growth in an agricultural field might be due to tillage operations, influence of natural soil fertility and physical structure, topography, crop stress, irrigation practices, incidence of pest and disease etc. Effective management of the crop variability within the field can enhance financial returns, by improving yields and farm production and reducing cost of production. Various inputs to the farm such as fertilizers, irrigation, pesticides, seeding, etc. can be adjusted and applied precisely according to the variability in soil properties and crop growth (Atherton et al., 1999).

A farmer or agronomist can program a UAV to fly a directed path whenever they want. This allows a crop to be monitored for things that might be of interest in the growth of the plant. UAVs are capable of providing ultra-high resolution images, video capturing and NIR photography. The potential application of UAVs in agriculture is limitless. Some of them are as under:

- Identifying and monitoring the spread of crop destroying weeds/pests
- Monitoring the crop health
- Nitrogen content mapping, soil brightness mapping
- Crop cover, Biomass estimation, yield prediction.

Aerial images have been widely used for crop yield prediction before harvest. These images can provide high spatial cloud free information of the crop's spectral characteristics. Analysis of vegetation and detection of changes in vegetation patterns are important for natural resource management and monitoring, such as crop vigour analysis. Healthy crops are characterized by strong absorption of red energy and strong reflectance of NIR energy. The strong contrast of absorption and scattering of the red and near-infrared bands can be combined into different quantitative indices of vegetation conditions.

Biophysical parameters such as plant height and biomass are monitored to describe crop growth and serve as an indicator for the final crop yield. Multi-temporal Crop Surface Models (CSMs) provide spatial information on plant height and plant growth.

1.2 Problem Statement

Remote Sensing data provides high quality spatial and temporal information about land surface features which include the environmental impacts on crop growth conditions. It has been proved to be an effective tool to assess and monitor vegetation parameters, crop vigour and yield estimation.

However, the problem lies in the fact that most of the studies are conducted at a national/regional level covering very large areas. The use of low resolution images have resulted into generalisation of the crop condition and yield estimates. The coarse resolution also had a mixture of crops and other non-crop vegetation that was later correlated to the final crop yield.

On the other hand, relatively few studies have been conducted based on the relationship between remote sensed data and field scale crop yield. At this particular stage, the yield or agricultural production is a result of several complex factors that use other external parameters to compute the yield.

Agricultural production is also influenced by the following variabilities: yield variability, field variability, soil variability, crop variability, anomalous factor variability and management variability (Oliver et al., 2013; Zhang et al., 2002). Those variabilities result in differences in crop growth within agricultural fields that can be quantified by monitoring crop canopy variables throughout the growing season. Important variables in this context include leaf area index (LAI), biomass, and nitrogen status (Hansen and Schjoerring,2003; Serrano et al.,2000).

Also, the crop insurance claim is usually calculated on the basis of crop cutting experiments. Therefore there has always been a problem in getting timely and accurate data, due to which payment of claims to farmers were getting delayed. Currently claim adjusters often have to physically walk out into a field to measure the extent of crop damage.

Therefore, developing an assessment tool with the aid of UAV acquired imageries that will not only compute the yield potential of a particular crop but also estimate the amount of crop insurance that can be paid to farmers.

1.3 Specific Objectives

The major objectives of this study are as follows:

1. To develop a remotely sensed vegetation index based yield model for a corn crop using high resolution airborne imagery.

2. To identify the crop cover, detect the presence of weeds that affect the growth of crops and its subsequent yield.

3. To compare the yield estimated from the UAV data with the existing yield estimating technology.

2. Literature Review

Monitoring agricultural crop conditions during the growing season and estimating the potential crop yields are both important for the assessment of seasonal production.

Accurate and timely assessment of particularly decreased production caused by a natural disaster, such as drought or pest infestation, can be critical for countries where the economy is dependent on the crop harvest. Early assessment of yield reductions could avert a disastrous situation and help in strategic planning to meet the demands.

2.1 Defining Precision Agriculture or Farming

The American National Research Council defined precision agriculture (or precision farming) as "a management strategy that uses information technology to bring data from multiple sources to bear on decisions associated with crop production". It is commonly admitted that it encompasses all the techniques and methods of crop and field information gathering that help taking into account in crop management the local and site-specific heterogeneity. Remote sensing image products, such as biophysical parameters maps for instance, have proven to be of high information content for that purpose, especially thanks to their spatial dimension. Vegetation indexes, derived from accurately calibrated remote sensing images, can help producing such maps by means of empirical or modelled relationships. They are now widely used by the remote sensing community especially to provide coupled agronomical and spatial information about cereal crop status like wheat. Such products are then often assimilated in crop models to derive more complex crop stress information or even directly integrated into a Geographical Information System for precision practices management.

2.2 Conventional Ground-Based Techniques

This technique was more common in the past when current technologies were not available. The traditional approach of data collection for crop monitoring has involved ground-based visits and reports. These conventional techniques are subjective, time consuming and complex resulting in information being available very late, usually after harvesting. Also, they are prone to large errors due to incomplete ground observations leading to poor crop yield assessment and crop area estimations. Even at present in India, crop yield estimation and yield loss due to natural calamity is calculated based on field reports and assessment of crop-cutting experiments by district and block agriculture officers. Since these reports are often mired in inconsistencies, insurers end up processing inadequate claims.

2.2.1 Crop Cutting Experiment

The traditional approach of crop estimation involves a complete enumeration for estimating crop acreages and sample surveys based on crop cutting experiments for estimating crop yield. The yield surveys are fairly extensive with plot yield data collected under a complex sampling design that is based on a stratified multistage random sampling design.

Nielsen (2004) studied the yield component method, which is the most simple and common technique to estimate crop yield. This technique involves a stratified random sampling procedure. The yield sample locations are selected from each of the study fields and the average yield obtained from each sampling site would be used to calculate per acre yield.

The techniques of crop cutting vary greatly in different parts of the world. The techniques used are dependent upon a number of factors. These factors include the administrative setup, type and size of field staff, farmer cooperation, crop practices, and harvest conditions. Consequently, it is not possible (nor desirable) to lay down a single uniform approach for crop-cutting surveys. However, all crop-cutting surveys do have one element in common. One or more plots (or groups of plants) are chosen as samples from commercial fields. The plots comprise only a small fraction of the total area in the field. Therefore, it is not possible to estimate the yield in an individual field with acceptable statistical precision unless many plots are selected. The yields calculated from one or two plots in a field are not highly correlated with the yield for the entire field because the mean of all plots in a field is statistically independent of the individual plots. Where it is desired to estimate or compare yields for individual fields, the number of plots needs to be large. For instance, small field plots consisting of less than 200 square feet have a within-field coefficient of variation of approximately 20-25 percent for yield per acre. Therefore, an estimate of yield for an individual field would require around 20-25 units per field to achieve a standard error of the mean equivalent to a coefficient of variation of 5 percent.

In general, measuring yields annually by crop cutting for small political or many administrative districts within a country is too costly. However, attempts have been made to employ auxiliary data or double sampling involving a large number of fields as a basis for adjusting a smaller crop-cutting survey to obtain current yields for small geographic regions. Typically, eye estimates of yield per acre are made for many fields and a random subsample of fields for crop cutting is taken.

In case of corn, the estimated yield is calculated by multiplying the year number by average row number by kernel number and then dividing the result by 90, which represents the average kernel weight. For other sampling sites the same procedure described above was followed, and eventually the yield obtained from each sampling sites was averaged to obtain the estimated yield for the entire field. This method, as said earlier, is time consuming, tedious, and inefficient as it does not account for the variation in field crop growth conditions.

2.3 Remote Sensing Techniques for Precision Agriculture

The use of remote sensing data for precision agriculture started in early 1980s. The data were used to study variations for crop and soil conditions. Remote sensing technology applications for monitoring vegetation condition has been studied extensively during the past several decades, providing timely assessment of changes in growth and development of agricultural crops.

Multispectral remote sensing plays a major role in precision agriculture due to its ability to represent crop growth condition on a spatial and temporal scale as well as its cost effectiveness.

Multispectral remote sensing significantly helps in exploring the relationships between crop biophysical data namely vegetation development, photosynthetic activity (PAR), biomass accumulation , leaf area index (LAI), and crop evapotranspiration (ET), with crop production (Jayanthi, 2003).

Many empirical relationships have been established in the past between spectral vegetation indices and leaf area index, fractional ground cover and crop growth rates through ground sampling. These relationships are then used by the crop growers to estimate the expected yield of crops prior to harvest in order to make crop management and production-related decisions for maximizing field productivity and market gains.

Crop production and yield estimation both have a direct impact on the economic development of a nation and food management (Hayes and Decker, 1996). Airborne multispectral remote sensing has been used in assessing the crop yield conditions. It has been often used in estimating crop yield for a variety of crops in the past years (Yang, Bradford, and Weigand, 2001; GopalaPillai and Tian, 1999). Singh et al. (1992) studied the use of satellite spectral data in estimating the crop yield surveys.

2.3.1 Satellite Imagery

With the successful launch of high resolution multispectral satellites, the use of satellite data in agriculture sector has increased tremendously. Although imagery is available from satellite systems, there are some distinct disadvantages associated with their use, such as higher cost for smaller spatial extent, as well as lower spatial and temporal resolution. Though satellite remote sensing covers large areas and the analysis can be done in a single image consuming less time, data can be recorded in different wavebands which provide accurate information about the ground conditions, readily available historical data and the data can be acquired without any administrative restrictions. Satellite images have problems like data masking due to cloud presence, lower spatial resolution, data not being available readily for real time management of crop growth due to fixed temporal frequency and correction of radiometric data because of atmospheric interference.

The normalized difference vegetation index (NDVI) derived from the visible and near-infrared (NIR) bands of the NOAA AVHRR satellite has been successfully used to monitor vegetation changes at regional scales (Tucker et al., 1983).

Temporal changes in the NDVI are related to net primary production (Malingreau et al., 1986; Goward et al., 1987; Prince, 1991). Tucker and Sellers (1986) provided a theoretical background to relate primary production estimates based on the absorption of photosynthetically active radiation (PAR) by the canopy. Satellite observations can also provide an estimate of biomass. Earlier field studies conducted by Daughtry et al. (1983) and Asrar et al. (1985) provided experimental validation of this theory that relates spectral reflectance to biomass production of vegetation at field and regional scales.

Remote sensing methods have been developed for non-destructive monitoring of plant growth and for the detection of many environmental stresses which limit plant productivity.

2.3.2 Aerial Platform and UAV Technology

In recent years, Unmanned Aerial Vehicles (UAVs) became widespread in RS (Colomina and Molina, 2914; Shahbazi et al., 2014). Van Blyenburgh (1999) defines UAVs as uninhabited, reusable, motorized aerial vehicles. UAVs rely on microprocessors allowing autonomous flight, nearly without human intervention (Nonami et al., 2010).

Modern airborne imaging technology based on unmanned airborne vehicles (UAVs) offers unprecedented possibilities for measuring our environment. For many applications, UAV-based airborne methods offer the possibility for cost-efficient data collection with the desired spatial and temporal resolutions. An important advantage of UAV-based technology is that the remote sensing data can be collected even under poor imaging conditions, that is, under cloud cover, which makes it truly operational in a wide range of environmental measuring applications.

2.4 Benefits of Drone Technology

Data collection with unmanned aerial vehicles (UAVs) have been known to fill a gap on the observational scale in remote sensing by delivering high spatial and temporal resolution data that is required in crop growth monitoring. The latter is part of precision agriculture that facilitates detection and quantification of within field variability to support agricultural management decisions.

A major advantage over satellite imagery is the independence of clouds and revisit time and fast data acquisition with real time capability (Berni et al., 2009; Eisenbeiss, 2009). Furthermore, high temporal resolution is given through high flexibility in data acquisition (Aber et al., 2010; Shahbazi et al., 2014). Those characteristics make UAVs highly suitable for many agricultural applications

(Jensen et al., 2007; Swain and Zaman, 2012). Compared to satellite remote sensing, aerial imagery is more applicable to precision crop management due to the following advantages:

- Images can be acquired frequently over the study area throughout the crop growing season,
- Image acquisition can be rescheduled to a cloud free day if there is data mask due to cloud on the day of acquisition,
- Superior resolution- high spatial resolution showing soil and crop growth variability,
- Cost per acre is relatively low when scanning large areas

Though aerial remote sensing is more relevant to precise crop management in terms of resolution, it does have problems like band to band registration, geo-rectification and mosaicking of images that involve manual efforts, bidirectional reflectance variations, and lens vignetting effects. Apart from these issues, aerial remote sensing offers the best soil and crop growth variability information with very high spatial resolution less than 0.5 m something which satellite sensors cannot.

In areas with mixed cropping pattern, aerial remote sensing can be effectively used to delineate the crop type and land use. Drones can also be used effectively in crop insurance—not only to determine the actual cultivable land, but also during the claims process to understand the extent of loss and the actual yield. The high resolution imagery from drones will help in getting accurate data to enable crop insurance companies to give proper compensation to affected farmers.

The benefits of UAVs surpass its disadvantages in ways like:

- When equipped with high precision cameras, they can help adjusters understand the true health of a field using a multispectral sensor.
- With their ability to cover distances quickly, drones can reduce the time it takes to settle claims from days to hours.
- Based on weather trends, drones can also be proactively positioned in areas of high claim activities and deployed the moment a new order comes in.
- Additionally, since drones can relay information back to remote specialists in real time, more claims can be resolved within a shorter time frame, making for a faster and streamlined insurance process.

In the current scenario, it is very important to validate the satellite data with the existing aerial images so as to develop a new and hybrid image analysis method that can provide precise remote sensing inputs to facilitate irrigated agriculture at different scales needed for precision agriculture. Also it becomes essential to address the complexity of issues in handling and acquiring these spatial and temporal remote sensing imagery.

RS provides such timely information for assessing within field variability to adapt agricultural management purposes (Atzberger, 2013).

2.5 Understanding Corn Phenology

An understanding of the developmental processes of a corn plant is important in evaluating its yield potential. Surveying crop growth during phenological stages is an important component of precision agriculture (Hansen and Schjoerring, 2003; Thenkabail et al., 2000). Remote sensing has great potential of contributing data for such kind of investigations in the field of precision agriculture (Mulla, 2013).

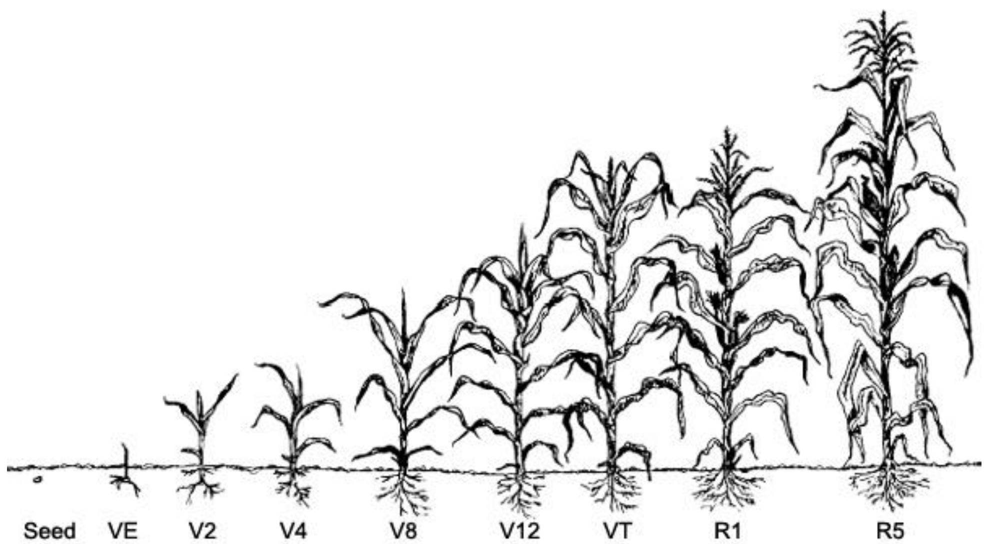


Figure 1: Corn Growth Stages

Vegetative Stages		Reproductive Stages	
Stage	Description	Stage	Description
VE	Emergence	R1	Silking - silks visible outside the husks
V1	One leaf with collar visible	R2	Blister - kernels are white and resemble a blister in shape
V2	Two leaves with collars visible	R3	Milk - kernels are yellow on the outside with a milky inner fluid
V(n)	(n) leaves with collars visible	R4	Dough - milky inner fluid thickens to a pasty consistency
VT	Last branch of tassel is completely visible	R5	Dent - nearly all kernels are denting
		R6	Physiological maturity - the black abscission layer has formed

Table 1: The Vegetative and Reproductive Stages of Corn

2.6 Use of Vegetation Indices

Remotely sensed spectral vegetation indices are widely used and have benefited numerous disciplines interested in the assessment of biomass, water use, plant stress, plant health and crop production. The successful use of these indices requires knowledge of the units of the input variables used to form the indices and an understanding of the manner in which the external environment and the vegetation canopy influence and alter the computed index values. Healthy crops are characterized by strong absorption of red energy and strong reflectance of NIR energy. The strong contrast of absorption and scattering of the red and near-infrared bands can be combined into different quantitative indices of vegetation conditions. These mathematical quantitative combinations are known as vegetation indices. Since the late 1980s, numerous studies like Funk and Budde have been conducted on crop growth analysis using normalized difference vegetation index (NDVI) to support precision agriculture.

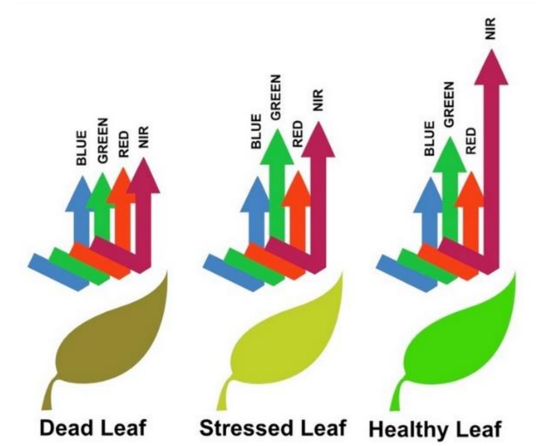


Figure 2: Reflectance Properties of Leaves in different stages

VIs are designed to provide a measure of the overall amount and quality of photosynthetic material in vegetation, which is essential for understanding the state of vegetation for any purpose. These VIs are an integrative measurement of these factors and are well correlated with the fractional absorption of photosynthetically active radiation (fAPAR) in plant canopies and vegetated pixels. They do not provide quantitative information on any one biological or environmental factor contributing to the fAPAR, but broad correlations have been found between the broadband greenness VIs and canopy LAI.

2.7 Crop Yield Monitoring

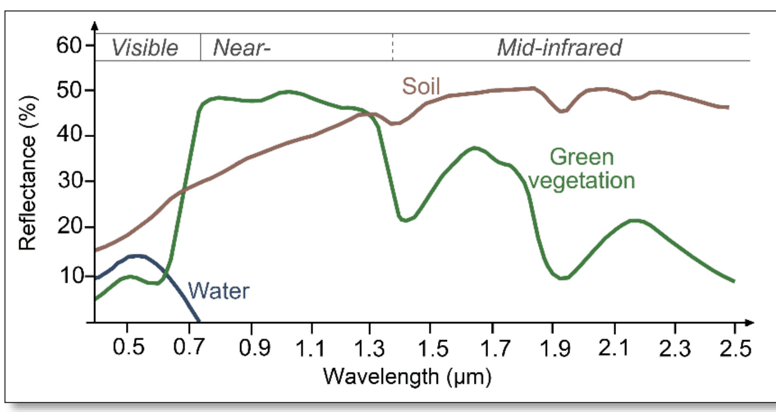


Figure 3: Spectral Reflectance Curve: Water, Soil, Vegetation

The spectral response from a crop can be well monitored using different spectral and spatial resolution depending upon the crop phenology and crop type. Several studies have shown that vegetation health can be very well measured using near infrared and red wavelength bands. Vegetation indices namely GNDVI, ENDVI are used by researchers all over the world to determine the status of healthy vegetation and differentiate from other land use changes. Healthy, dense vegetation appears brighter and reflects more radiation in the near infrared region of the spectrum whereas severely stressed vegetation appears dark and reflects less radiation.

Healthy vegetation will have a high GNDVI and ENDVI values because of high reflectance in the infrared and low reflectance in the red band due to absorption by chlorophyll in the leaves.

Crop growth and final yield estimation can be done by learning the land cover change that happens during the crop growing season and also throughout the year. Crop growth seasonal change provides information related to agricultural management and the annual changes provides information about the cropped area or land cover change. The spectral reflectance of different surfaces and land cover is presumed to be different.

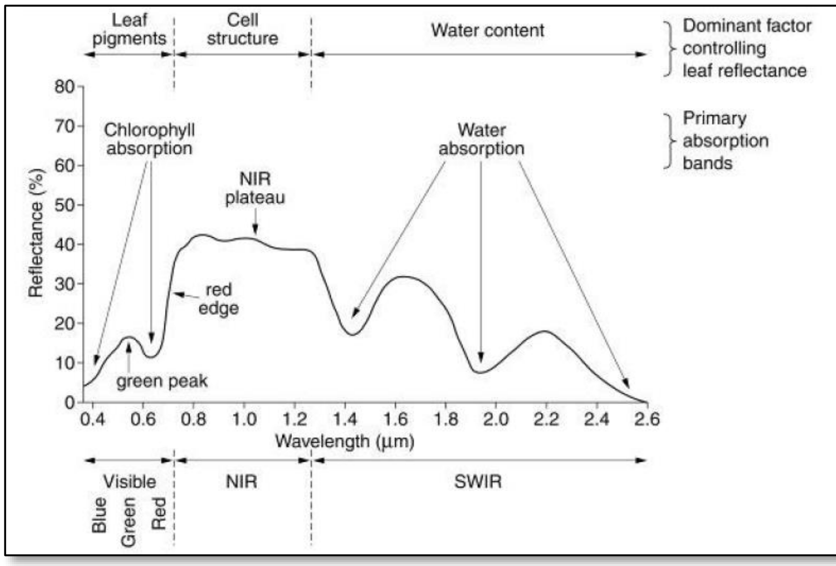


Figure 4: Spectral response characteristics of a healthy green vegetation

Healthy green vegetation has a unique spectral reflectance pattern based on the leaf structure and composition. In the visible part of the region, chlorophyll in a leaf absorbs light in the 0.45µm (blue) and 0.68µm (red) portion of the spectrum and absorbs less in the green part of the spectrum resulting in a small peak at 0.5-0.6µm that makes vegetation appear green to the human eye. Healthy vegetation reflects more in the near infrared region and relatively lower in the red region due to high photosynthetic activity and thus useful for vegetation classification and mapping. The moisture content in the leaf results in water absorption at 1.45µm and 1.9µm respectively. The spectral reflectance of a crop canopy is influenced by different factors such as the crop canopy structure, crop condition, leaf area index, cultural practices, soil moisture stress and crop growth stage (Verma et al., 1998).

Therefore, in recent years, the application of remote sensing techniques for crop yield estimation has been gaining importance due to the improvements in the spatial and spectral resolution of remotely sensed imagery. Crop growth and yield monitoring is important for the economic development of a country and with the aid of remote sensing it has becomes easier to monitor the area extent of agricultural crops.

2.8 Crop Insurance

A mechanism/ tool / arrangement through which farmers can protect themselves/ get compensation for loss or destruction of their crop due to events like flood, drought, pests, diseases or as a result of other natural disasters.

Crop insurance can be offered on an indexed basis, where claims are a function of a defined index chosen to be a good proxy for incurred crop loss or on an indemnity basis, where claims are based on actual crop losses. There is not yet a consensus amongst academics or practitioners as to the best form for crop micro insurance but leading contenders include weather index insurance, area yield index insurance and group stop loss indemnity insurance.

Weather Index Insurance: Claims payments from weather index insurance are a defined function of recorded weather at a contractual weather station and are triggered when the recorded weather breaches the pre-defined critical levels.

Area Yield Loss Index Insurance: Area yield loss index insurance claims are a function of average local yields for a specific crop, estimated through crop cutting experiments in a sample of local farms. Losses arising from yields falling below the average local yields are paid by the insurer. In a way, the area yield loss index insurance administered as a group policy combines the benefits of reduction of basis risks as actual losses are paid by insurer and also reduces moral hazard as individual farmers do not have an incentive to report lower or reduce crop output.

Group Stop Loss Indemnity Insurance: Here, claims are a function of the total crop loss incurred by a large group of farmers, who are joint policyholders

Area Yield Loss Index group of crop insurance models guarantees yield to the insured producer. The guarantee is a percentage of the yield calculated from historic yields (individual or group). Indemnities result from a shortfall of the guaranteed yield in the crop year insured. This yield shortfall is multiplied by an indemnity price selected by the insured before the insurance period begins.

3. Study Area

3.1 Physical Setting

Perth County is a county of the Canadian province of Ontario, and is located in south-western Ontario, 100 kilometres west of Toronto. Perth has an area of 10.36 sq. km is in the heart of Eastern Ontario's Rideau River Corridor, halfway between Ottawa - the Nation's Capital and Kingston.

Perth County is characterized by warm, reasonably wet summers and cold, snowy winters. Average daily temperatures range from a low of –7 C in January to a high of 20 C in July. There is, however, considerable variability around these averages. For example, a daily high of 14 C was recorded on January 14, 1995, while on January 4, 1981, the recorded daily high temperature was –32 C. Similarly, daily highs in July have ranged from 36 C to 4 C (Environment Canada 2005). Precipitation averages over 100 mm monthly from November through the end of January, while during the May to September growing season monthly precipitation averages between 80 mm and 100 mm. Again, variability in precipitation patterns occurs, with both dry spells and extreme precipitation events being possible; a single day storm event on July 28, 1983 brought 137 mm of rain to the area (Environment Canada 2005).

3.2 Agricultural Scenario

Perth County was selected for this study because it is an example of an established intensive agricultural area in Ontario, it has a large farming population and it was already familiar to the field researcher. Perth County is a predominantly rural municipality in southwestern Ontario, with a population of approximately 38,000. It is a very productive agricultural area, with 90% of the land in the County classified as prime agricultural land according to the Canada Land Inventory, with soils commonly being clay and silty loams (Perth County 2003). Agriculture creates 29% of the county’s employment, and farm gate sales total on average more than $400 million (Canada) annually (Cummings and Associates 2000).Stratford is located in Perth County, Ontario's richest agricultural region and one of the most agriculturally productive counties in all of Ontario. South-western Ontario is the heart of the country’s food belt, with soybeans and corn the two biggest crops. In Western Ontario, corn yields were 155.6 bushels/acre in 2014 which was down slightly from 157.3 bushels/acre in 2013. Western Ontario includes the counties of Peel, Dufferin, Wellington, Halton, Waterloo, Perth, Huron, Bruce, Grey and Simcoe.

Major Field crops in hectares, 2014

Crop	**Number of Hectares (2014)**
Corn for grain	44,061
Soy beans	39,552
Hay	28,283
Winter wheat	26,054
Corn for silage	10,362
Mixed grains	5,055
Dry white beans	4,111
Other dry beans	4,008
Barley and grain	3,741
Oats and grain	1,051

Table 2: The area covered by different crops

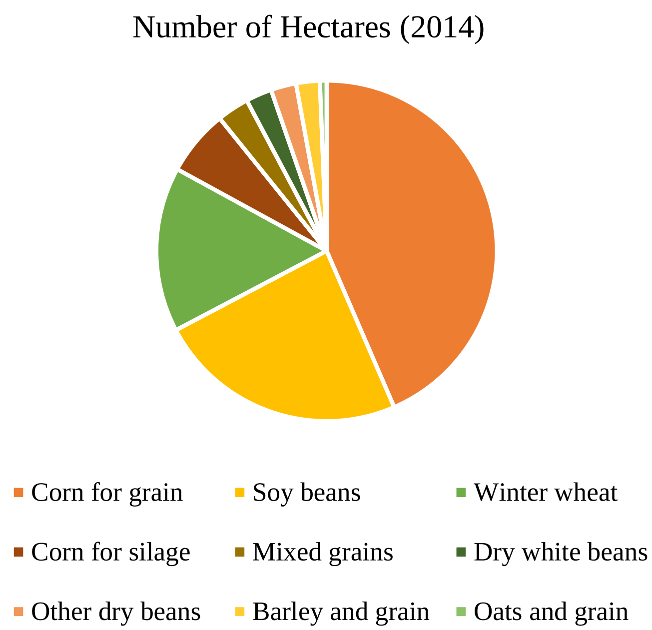


Figure 5: Chart showing the importance of corn in Perth

Perth County farmers are very aware of existing climate-related risks that affect their operations. However, they are generally unaware of or, in many cases, unconcerned about the potential effects of climate change. In part this likely reflects the conventional description of climate change in the sector—small increases in average temperature over several decades. However, lack of concern regarding climate change does not necessarily increase farmers' vulnerability to future climate risks. Farmers are continually responding to inter-annual climatic variability and employing adaptations to reduce their vulnerability to climate risks; a capacity to adapt to current climatic variability offers a certain level of preparedness for future climate changes. The capacity can be further enhanced by identifying and overcoming factors that constrain adaptation.

Therefore, an assessment tool that will help them the farmers in protecting their fields from the climatic variability is the main aim for the study.

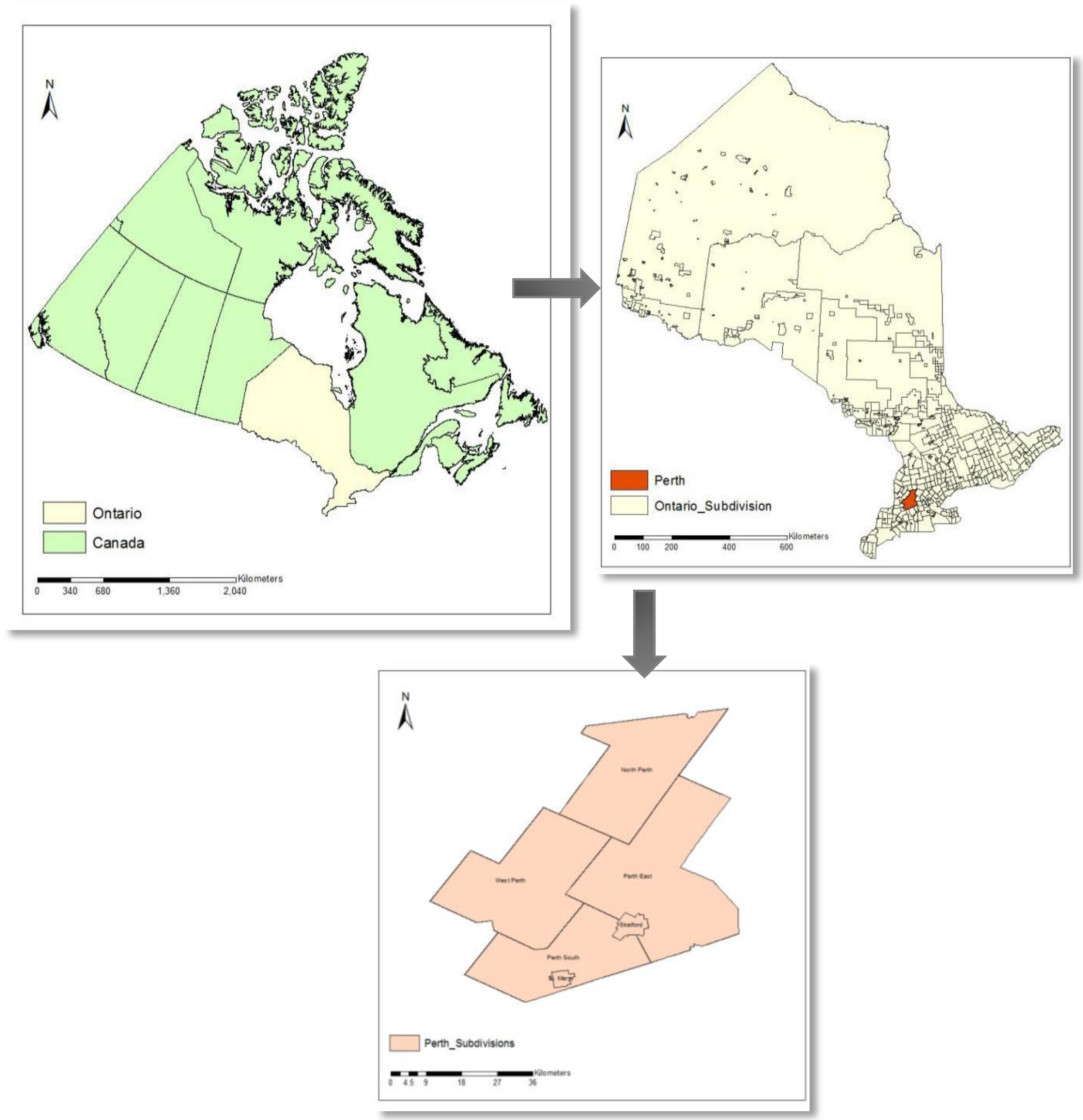


Figure 6: Study Area

3.3 Datasets

The area of interest or the plot of land used for the study lies within the Northern subdivision of Perth County, Ontario, Canada. For the purpose of study, images that have been acquired over the growing season of a corn plantation of a particular plot of land have been used. Images were collected using both RGB and BGNIR sensors at an altitude of 50 meters having an image resolution of 1.3 cms. The sample dataset for both the sensors have been displayed below:

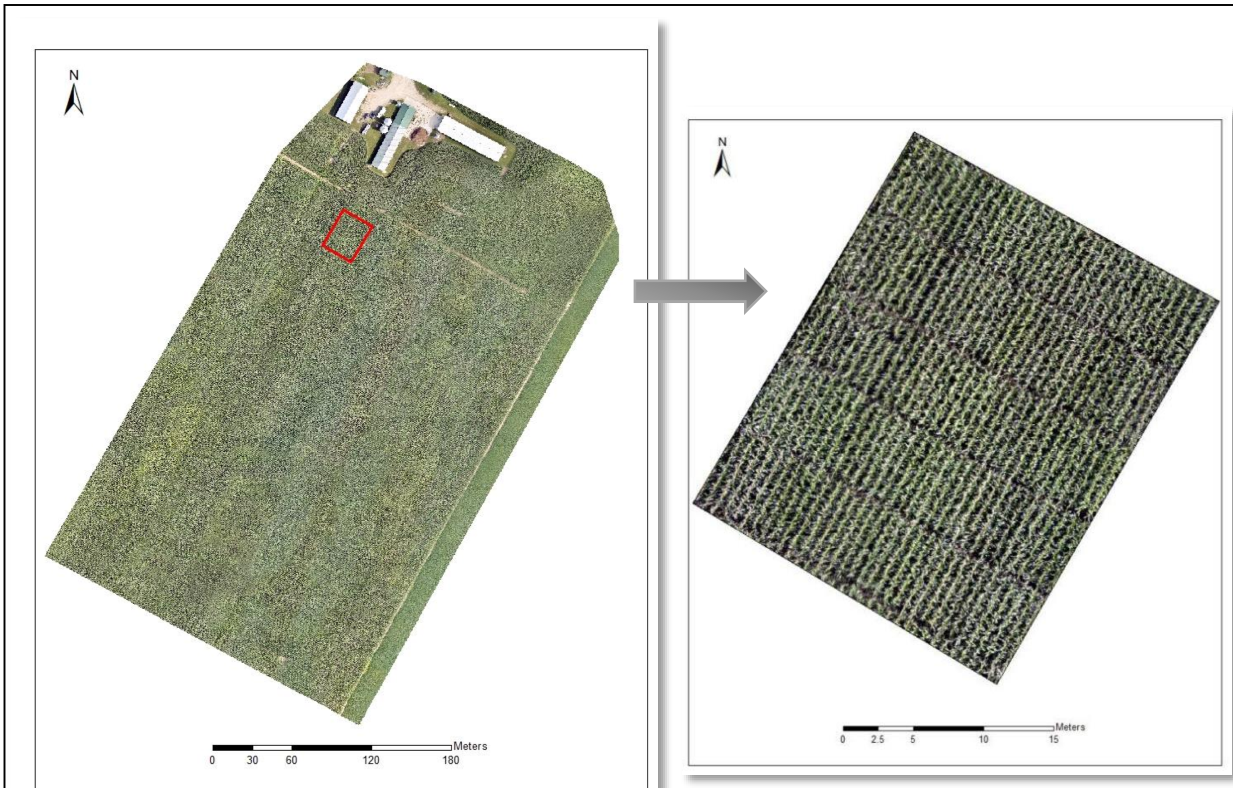
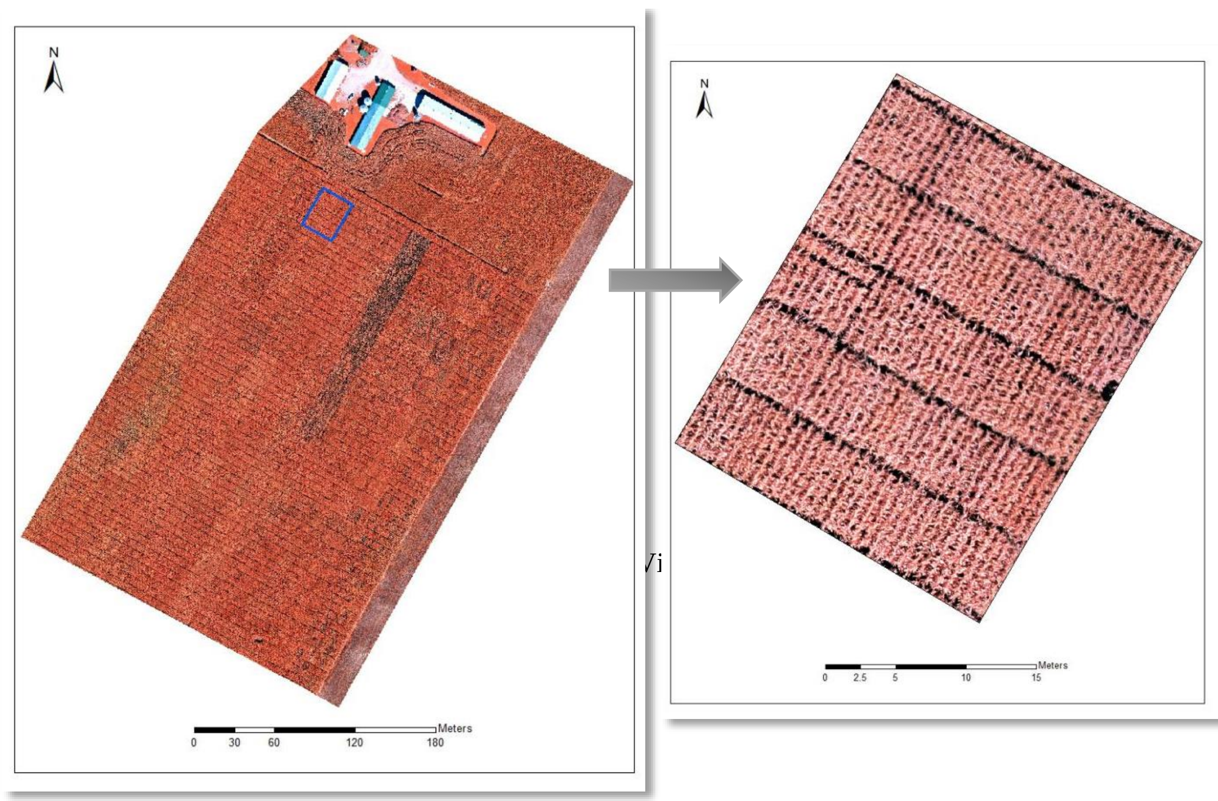


Figure 7: Sample Dataset- RGB and BGNIR Sensor



3.4 Season Monitoring

Surveying crop growth during phenological stages is an important component of precision agriculture (Hansen and Schjoerring, 2003; Thenkabail et al., 2000).

For the purpose of study, images of the same area of interest has been captured three times throughout the growing season of the corn crop. The multi-temporal image collection has helped us in determining the increase in the biomass content and monitoring the crop growth throughout its growing season. Images were collected in June, September and October i.e. during early season, mid-season and pre-harvest. This helps farmers in identifying the anomalies or threats during the growing season of the crops and take actions which helps in improving its crop productivity and yield.

Figure 8: Early Season

June, 2015

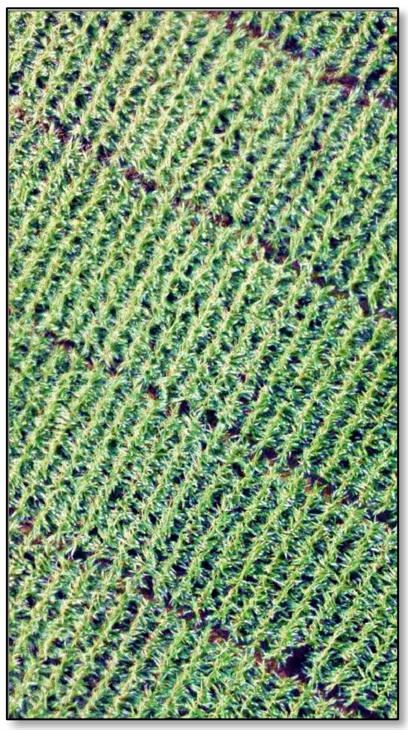


Figure 9: Mid-Season

September, 2015

Figure 10: Pre Harvest

October, 2015

A way to monitor plant growth is the idea of generating multi-temporal crop surface models (CSMs) to allow for comparison of different phonological stages (Bendig et al., 2013; Hoffmeister et al., 2013), which has been demonstrated later in the project.

4. Data Acquisition

The use of Unmanned Aerial Vehicles (UAV) imagery for GIS data acquisition is constantly evolving. The ease of use, agility of flying , lesser time for generating accurate data, and lower data acquisition costs have made UAVs very popular all over the globe .The accuracy of aerial data acquired using the UAV is directly related to the spatial resolution of the input imagery. The high resolution images from UAV can compete with traditional aerial mapping solutions that requires highly accurate alignment and positioning sensors on board.

A radio- controlled UAV based low- altitude remote sensing (LARS) platform was used to acquire quality images of high spatial and temporal resolution in order to estimate yield and total biomass.

4.1 Platform

PrecisionHawk provides a completely autonomous UAV, performing low altitude aerial data collection and subsequent data management and analysis. Backed with artificial intelligence and in-flight diagnostic / monitoring solutions as well as hardware such as processors and interfaces, UAV optional add-ons, sensors and a low altitude tracking and avoidance system, it has not only been able to automate the data collection itself through autonomous flight and sensor triggering, but it has also discovered how to produce high quality of data .

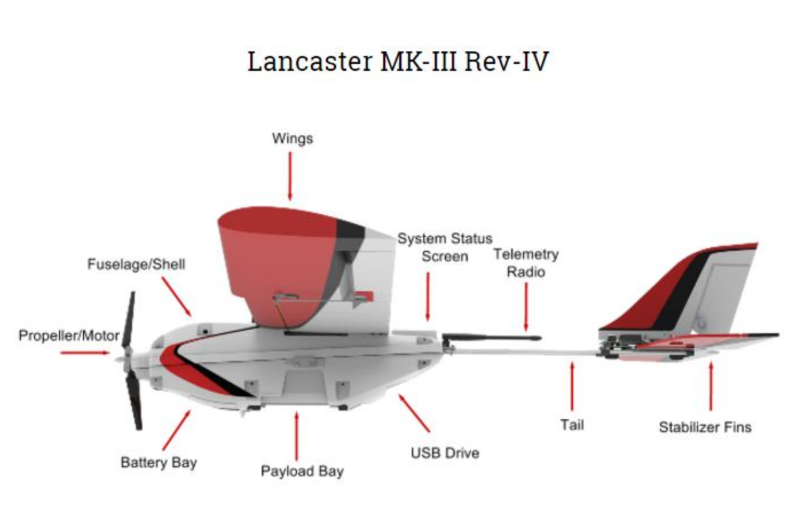


Figure 11: PrecisionHawk

4.2 Sensors Used

Sensor	Band Combinations	Ground Resolution
Visual (RGB)	Band1: Red Band2: Green Band3: Blue	0.7 cm/ pixel at 50 m altitude
Multispectral (BGNIR)	Band1: Near Infrared Band2: Green Band3: Blue	

Table 3: Sensor Information

4.3 Data Processing

Generally, two types of software are used for image processing: traditional photogrammetry software or computer vision software. Examples for photogrammetry software are Leica Photogrammetry Suite (LPS) and PhotoModeler. The photogrammetric approach starts with camera calibration, followed by ground control point (GCP) identification and tie point research either automatic or manual depending on the software (Sona et al., 2014). GCPs are points of known ground coordinates that facilitate georeferencing. Additional tie points identified by the software support the process. In a next step, exterior image orientation is estimated based on known interior image orientation. Exterior orientation is defined by X, Y and Z coordinates of the sensor and the UAV's roll, pitch and yaw (Aber et al., 2010). Roll equals the rotation around the X axis, pitch equals the rotation around the Y axis and yaw equals the rotation around the Z axis. Interior image orientation is defined by focal length, principal point location, three radial and two tangential distortion coefficients. Finally a bundle adjustment, the orientation of an image block, is carried out (Remondino et al., 2014). Difficulties arise during image georeferencing and bundle adjustment when image positions differ from those common for classical aerial surveys. Leica LPS was initially tested on data acquired for this study but arising problems during data processing led to a change to computer vision software.

Processing with computer vision is usually faster but reduces the user's control over georeferencing and block formation as well as calculated accuracies (Remondino and Kersten, 2012). Nevertheless, results are competitive with those from the photogrammetric approach (Sona et al., 2014). Available software packages include Pix4D Pro (Switzerland), Bundler and Agisoft PhotoScan Professional (Agisoft LLC, Russia). Pix4D Pro is chosen because it produces high quality results (Doneus et al., 2011; Gini et al., 2013; Neitzel and Klonowski, Sona et al., 2014)

4.4 Pix4D Processing

Pix4Dmapper is an image processing software that is based on automatically finding thousands of common points between images. The steps followed in Pix4D to process the images captured by UAV includes:

Each characteristic point found in an image is called a keypoint. When 2 keypoints on 2 different images are found to be the same, they are matched keypoints. Each group of correctly matched keypoints will generate one 3D point. When there is high overlap between 2 images, the common area captured is larger and more keypoints can be matched together. The more keypoints there are, the more accurately 3D points can be computed.

In cases where the terrain is flat with homogeneous visual content such as agriculture fields, it is difficult to extract common characteristic points (keypoints) between the images. In order to achieve good results:

- The overlap between images have been increased to at least 85% frontal overlap and at least 70% side overlap.
- Accurate image geolocation have been provided. The GCPs have helped in increasing the accuracy of the image location.

4.4.1 Workflow

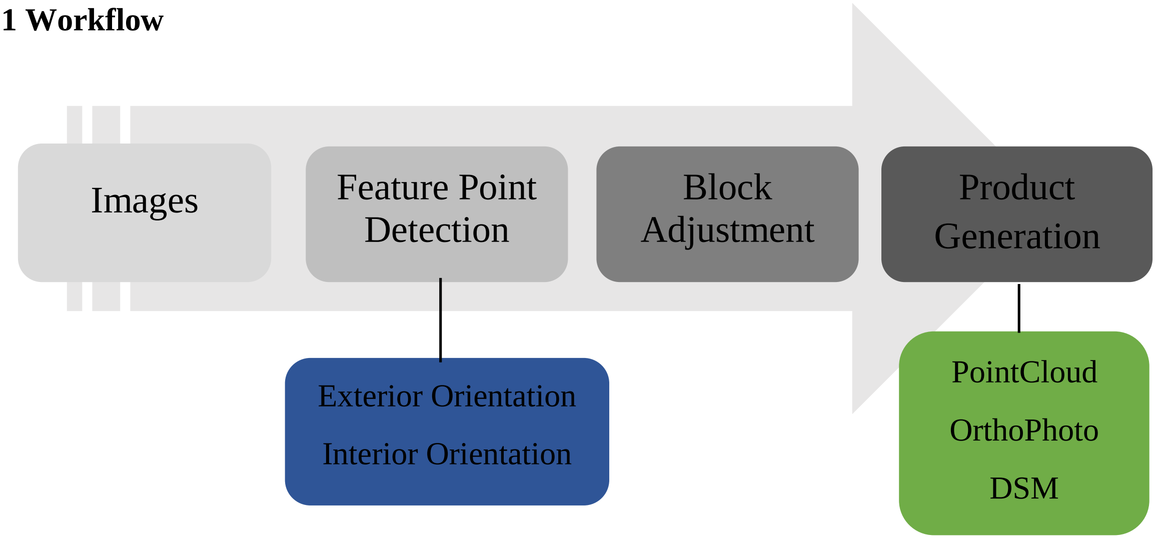


Figure 12: Image Processing Workflow

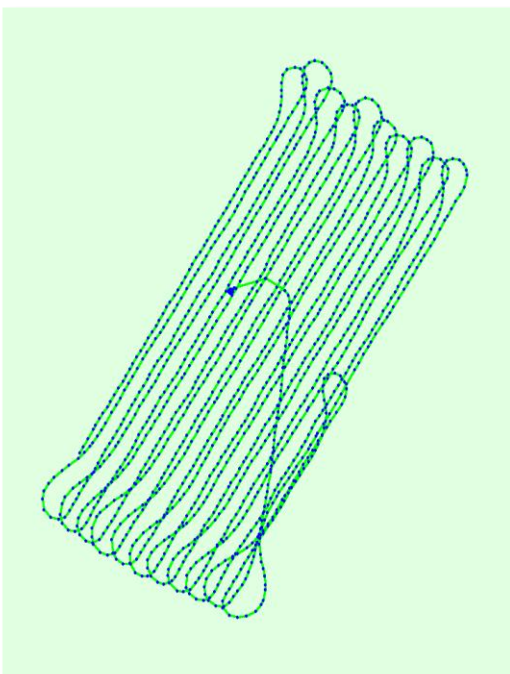


Figure 13: The Flight Plan showing Initial Image Positions

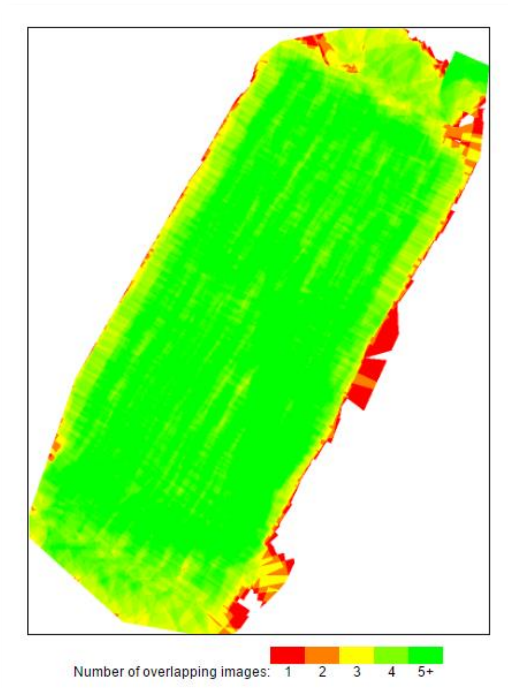


Figure 14: Number of overlapping images computed for each pixel of the orthomosaic. Red and yellow areas indicate low overlap for which poor results may be generated. Green areas indicate an overlap of over 5 images for every pixel.

Ground Control Points

A Ground Control Point (GCP) is a characteristic point whose coordinates are known. GCPs are used to georeference a project and reduce the noise. 3 GCPs is the minimum to geolocate (scale, orient, position) a project. Optimal accuracy is usually obtained with 5 - 10 GCPs. The GCP report is a part of the quality report and it shows the locational accuracy and the RMSE of the orthomosaic.

GCP Name	Accuracy XY/Z [m]	Error X [m]	Error Y [m]	Error Z [m]	Projection Error [pixel]	Verified/Marked
1 (3D)	0.020/ 0.020	-0.034	0.041	-0.001	1.624	9 / 9
3 (3D)	0.020/ 0.020	0.010	0.003	-0.000	1.267	10 / 10
4 (3D)	0.020/ 0.020	0.024	-0.043	-0.000	2.050	9 / 9
Mean [m]		-0.000258	0.000234	-0.000494		
Sigma [m]		0.024603	0.034518	0.000258		
RMS Error [m]		0.024605	0.034519	0.000557		

Localisation accuracy per GCP and mean errors in the three coordinate directions. The last column counts the number of images where the GCP has been automatically verified vs. manually marked.

Table 4: Geolocation Accuracy

4.4.3 Deliverables

Orthomosaic

This is a seamless (continuous) navigable visual Imagery of the project. It is a file that represents the full georeferenced image and its associated world file. Each point contains X, Y and colour information. The orthomosaic has uniform scale and can be used for 2D measurements (distances, areas).

Digital Surface Model

The DSM (Digital Surface Model) is a 2.5 D model of the mapped area. Each pixel of the raster GeoTIFF file and each point of the vector point cloud contain (X, Y, Z) information. They do not contain colour information. By definition, digital surface models (DSMs) represent the spatial distribution of terrain attributes. It is a file containing elevation values representing the terrain height. Such models are needed for plant height (PH) and plant growth (PG) analysis with CSMs.

Figure 15: Orthomosaic

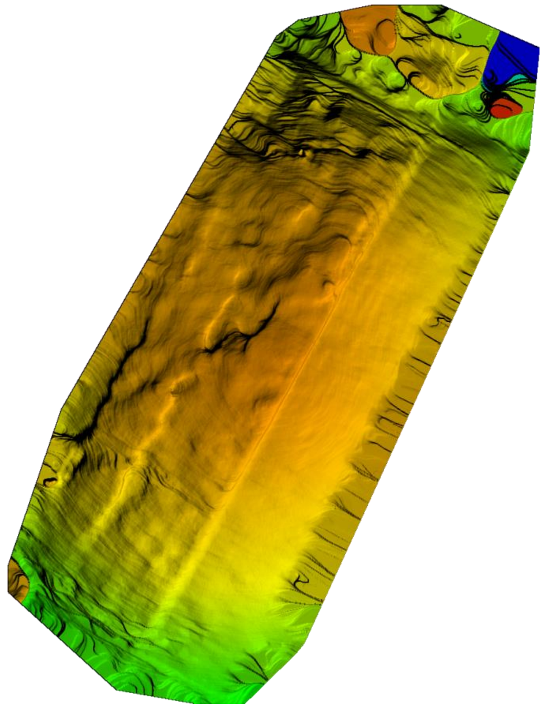


Figure 16: Digital Surface Model

Densified Point Cloud

The densified point cloud is a set of 3D points that reconstruct the model. The X, Y, Z position and the color information is stored for each point of the densified Point Cloud. The densified point cloud is computed based on the Automatic Tie Points and it provides a very accurate background for distance, surface and volume measurements.

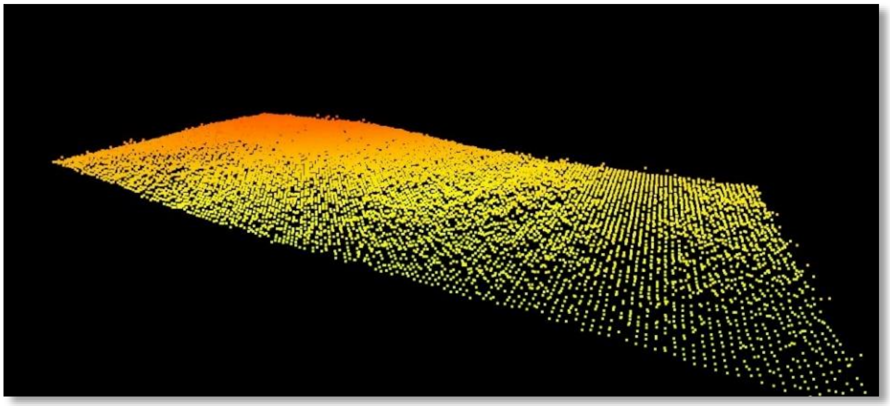
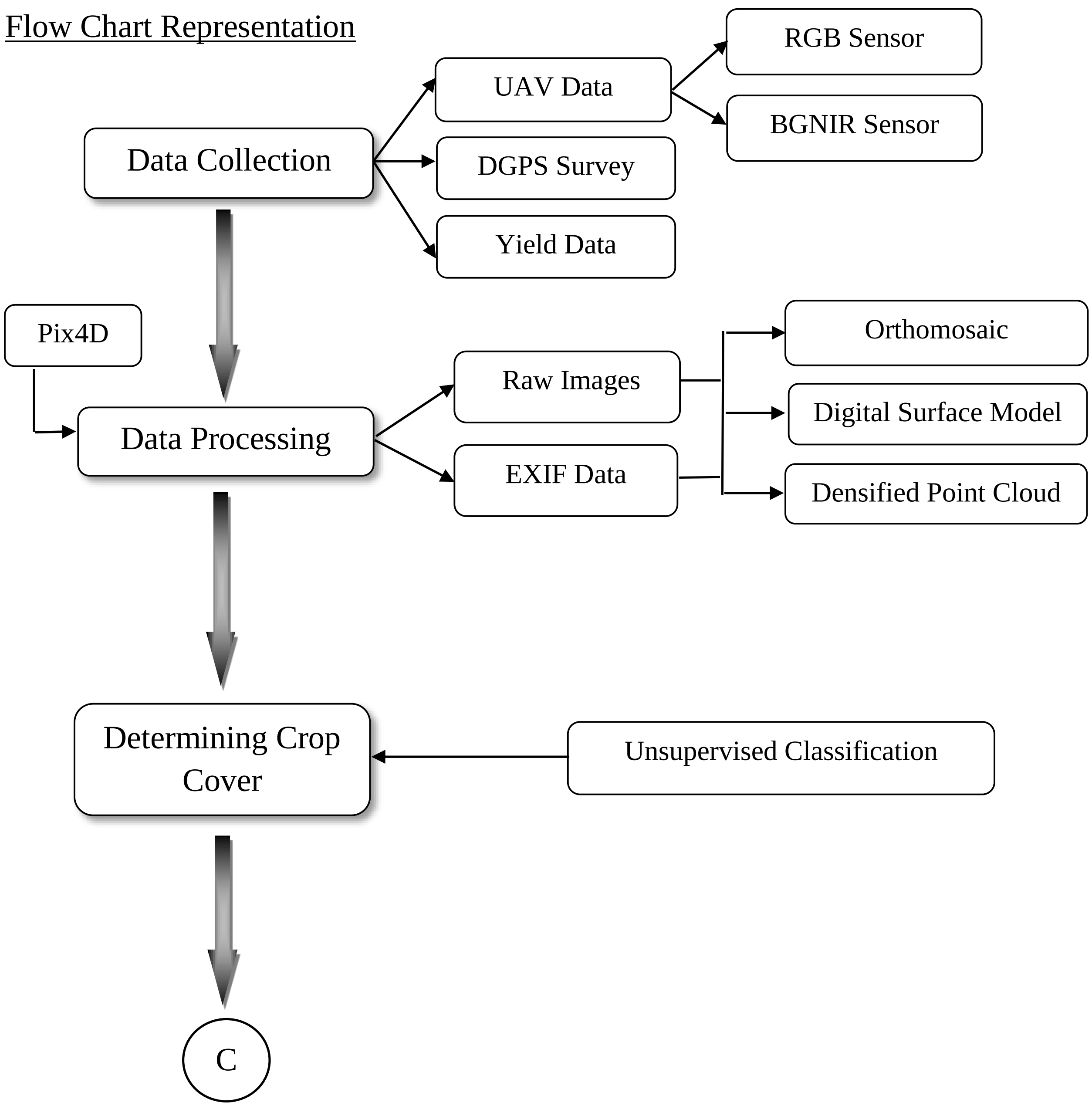


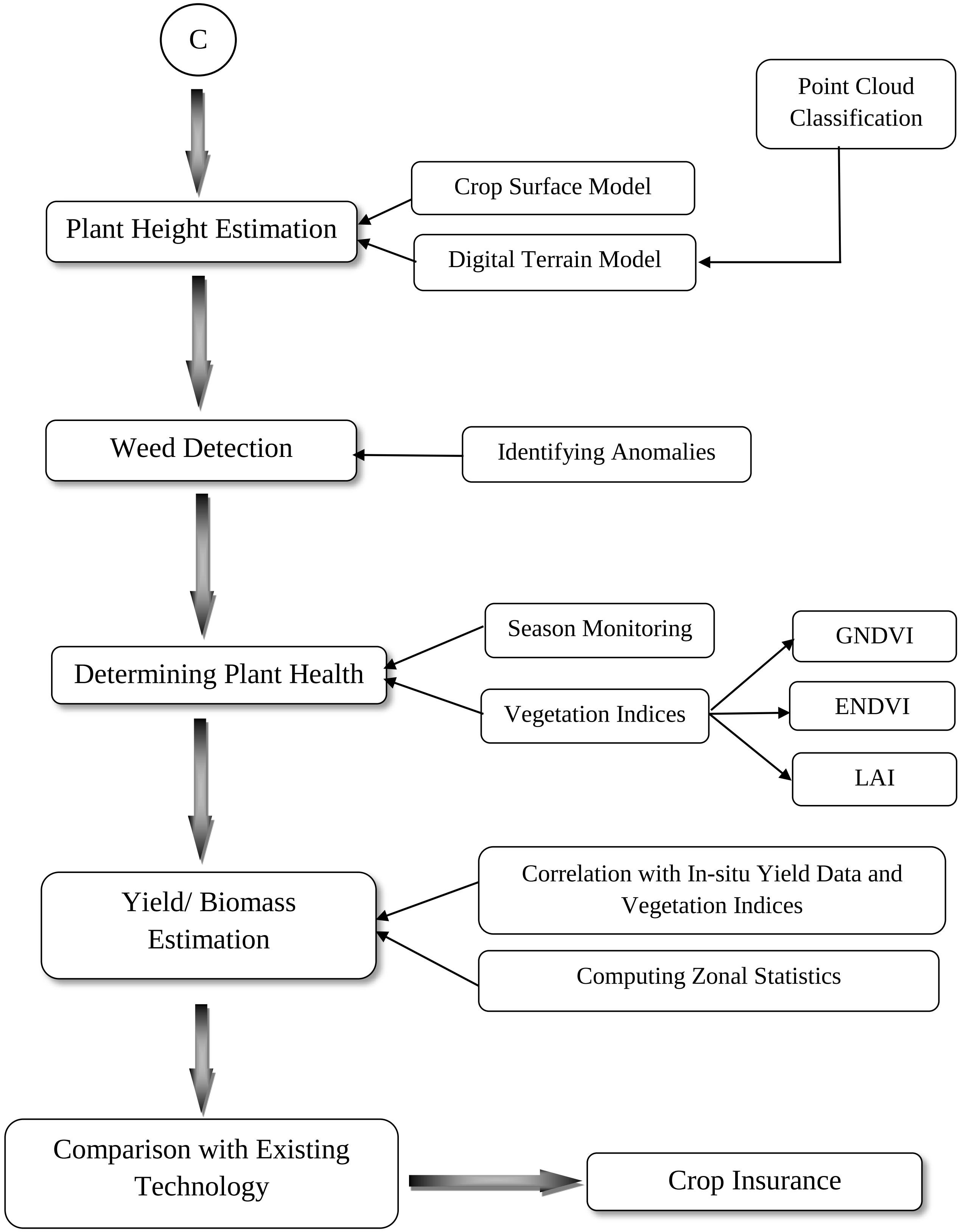
Figure 17: Point Cloud

5. Methodology

The methodology framed show the several aspects which can be used for yield estimation without extensive field work. The above methodology is followed to determine the health of the crop using remote sensing techniques on an aerial platform. This demonstrates how this technology can be simpler and time-saving as compared to the conventional techniques used for yield estimation and subsequent determination of crop insurance for farmers.

Flow Chart Representation




C
Point Cloud Classification
Crop Surface Model
Plant Height Estimation
Digital Terrain Model
Weed Detection
Identifying Anomalies
Season Monitoring
GNDVI
Determining Plant Health
Vegetation Indices
ENDVI
LAI
Correlation with In-situ Yield Data and Vegetation Indices
Yield/ Biomass Estimation
Computing Zonal Statistics
Comparison with Existing Technology
Crop Insurance

6. Results and Analysis

6.1 Crop Cover

This was computed to accurately delineate the vegetated area. This helps in computing the percentage of foliage cover per area. The crop cover is an important indicator of stage of growth and crop water use in crops.

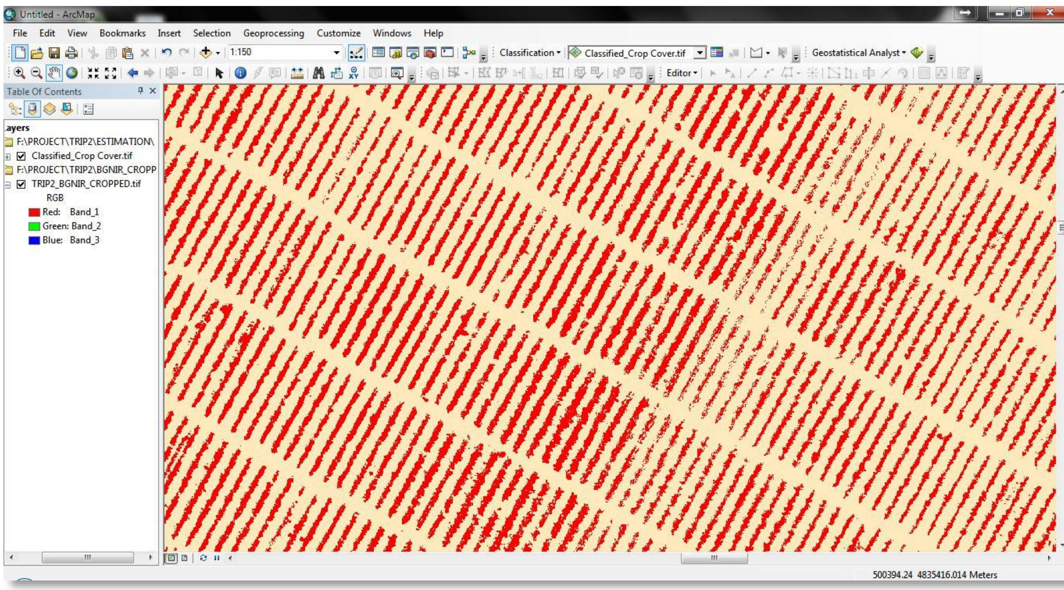


Figure 18: June, 2015

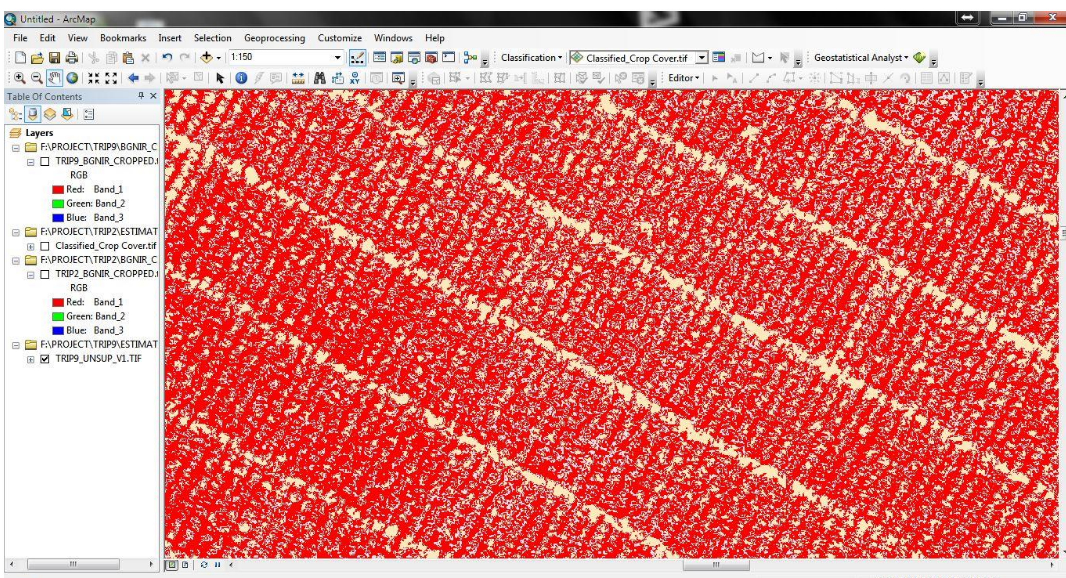


Figure 19: September, 2015

From the above images, the increase in the crop cover has been extracted by performing unsupervised classification in ArcGIS where the area covered by crops has been determined. The crop area was then converted into polygons to determine the exact foliage cover. The total study area was 0.13 square kilometres. The foliage cover or the greenness of the vegetation was found to increase from 0.0136 square kilometres to 0.0964 square kilometres.

6.2 Plant Height Estimation

Obtaining accurate and timely crop height estimates is important to characterize plants' growth rate and health. Agricultural researchers use this data to measure the impact of genetic variation in the crops on drought resistance and responses to environmental stresses. Practitioners also use crop height information to assess crop development and plan treatments. These measurements are currently obtained through manual measurement, or by driving heavy equipment through the field. These collection methods are time consuming and damaging to the crops (i.e. destructive testing), and as such, are not regularly used.

Measuring crop's height requires height estimates of the top of the crop and the ground, the difference of which is the crop height. Measuring crops from the air to characterize the top of the canopy benefits from unobstructed movement that does not damage the crops, but locating the ground is more challenging as layers of plants' leaves can obscure the ground.

Two generic ways adopted to reduce this error is:

- One way is to increase sensing power by using, for example, radars or powerful LiDARs.
- Alternative way is to fly a low altitude UAV with powerful sensors close to the plants, thereby exploiting the gaps in the crop canopy to directly sense the ground and the plants with lower heights.

By operating at low altitude, the system greatly increases the spatial resolution of the collected data, when compared to traditional approaches. Furthermore, the small size and weight of the system limits the risks of operating the unit.

In plant modelling, plant height (PH) is defined as the vertical distance from the model's origin to the uppermost point (Lati et al., 2013). For a plant canopy PH equals the difference between bare soil and the canopy top. Plant growth (PG) is defined by the difference in plant height between two observation dates. Both PH and PG are variables of interest in precision agriculture applications. PH is an important factor in optimizing site specific crop management and harvesting processes like crop yield predictions, precise fertilizer application, and pesticide application (Ehlert et al., 2009; Lati et al., 2013). Moreover, PH is a key variable in determining yield potential (Girma et al., 2005) and in modelling yield losses from lodging(Berry et al., 2003; Chapman et al., 2014; Confalonieri et al., 2011). Monitoring PG is important since plants undergo intra-annual cycles linked to growth and phenology (Atzberger, 2013).

Spatial coverage increases when PH is derived from 3D point clouds collected by Terrestrial Laser Scanning (TLS) (Hoffmeister et al., 2010; Lumme et al., 2008; Tilly et al., 2014) and airborne laser scanning (Hunt et al., 2003). Another way to derive such 3D point clouds is using UAV-based RGB imaging. PG is acquired by repeated measurements with the described methods and calculating the difference between observations. When analysing plant canopies, rather PH and PG information of a surface is required than point measurements.

Such information is provided within the concept of crop surface models (CSMs), first introduced by (Hoffmeister et al., 2010). By definition CSMs represent the top of the plant canopy at a given point in time (Hoffmeister et al., 2013). CSMs are accurately georeferenced and resolution typically ranges from 1 m to 0.01 m. PG is derived by subtracting surfaces at the start and the end of the desired observation period (Bendig et al., 2013). CSM

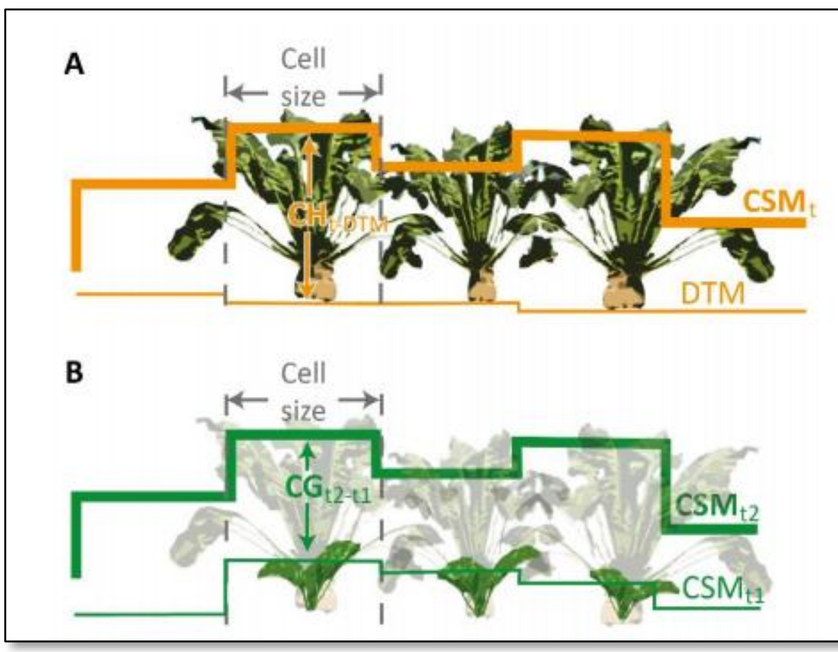


Figure 20: Deriving Crop Height by comparing CSM and initial DTM

products include PH and PG maps that enable spatial variability detection (Tilly et al., 2014). Point clouds for CSM generation are acquired through RS techniques like TLS or UAV RS. The latter is described in the following section

6.2.1 Crop Surface Models

Generating crop surface models requires:

1. Mosaicking of the collected images,
2. Point cloud generation,
3. Digital Terrain Model (DTM)
4. Digital surface model (DSM).

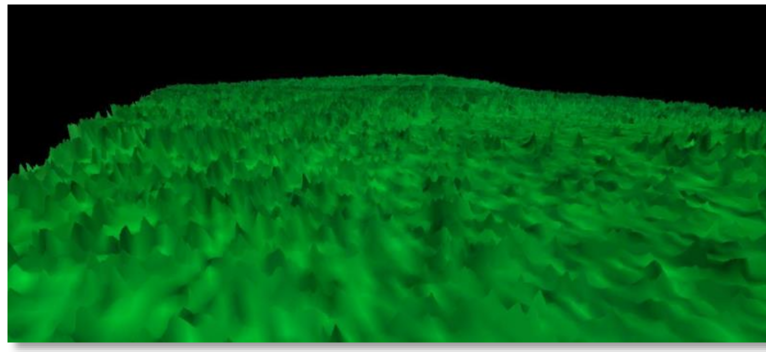


Figure 21: 3D Model of the Cropped Area

Here, the DSM represents the crop surface and is referred to as CSM hereafter. It has to be subtracted from a ground model (DTM) in order to obtain the Plant Height. The result is a 3D reconstruction of the geometry that displays a CSM. For enhanced absolute spatial accuracy, the GCPs were imported into Pix4D prior to mosaicking, where they were projected to all images automatically after being placed in a single image. We then manually verified and adjusted the positions if necessary. Finally, the CSM is exported in *TIF-image format.

6.2.2 Digital Terrain Model (DTM)

From the first level outputs generated i.e. the point cloud was further used to generate the Digital Terrain Model or the bare earth model. Bentley's Microstation V8 software was used to generate the DTM. The above ground points were classified and removed to derive the bare earth terrain.

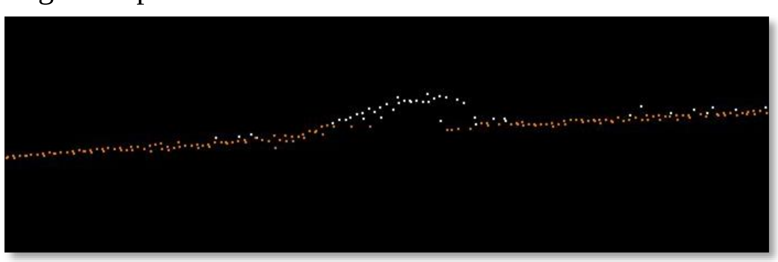


Figure 22: Classification of Above ground Points

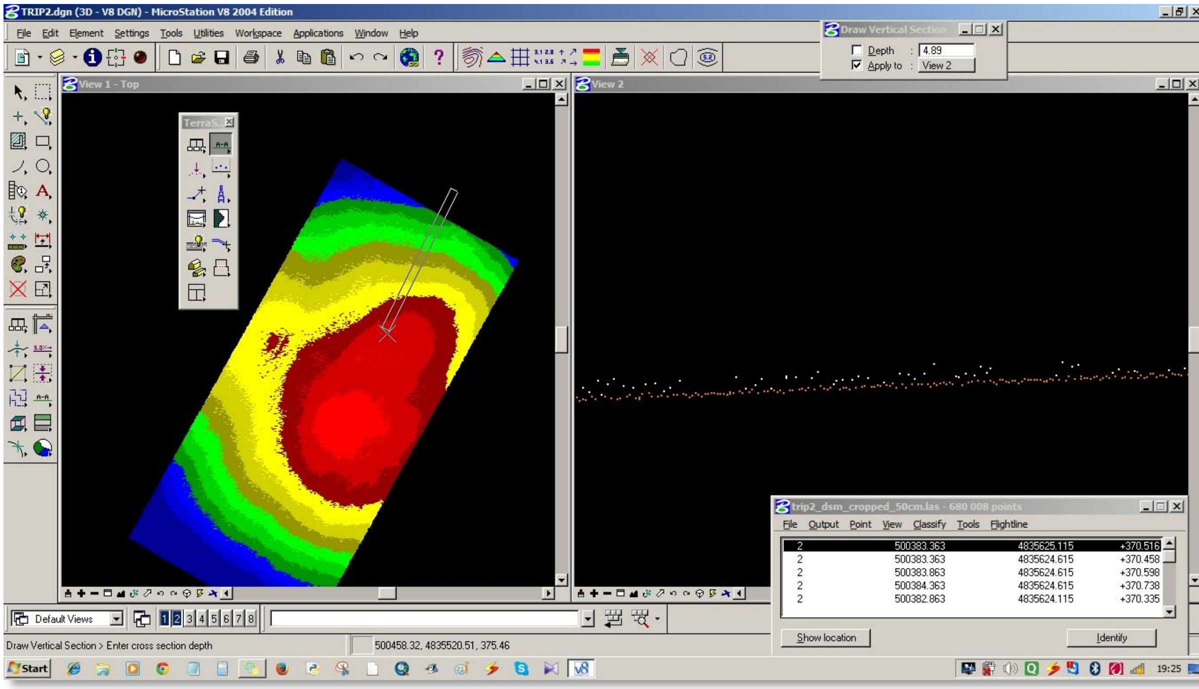


Figure 23: A cross-section showing the classified ground surface

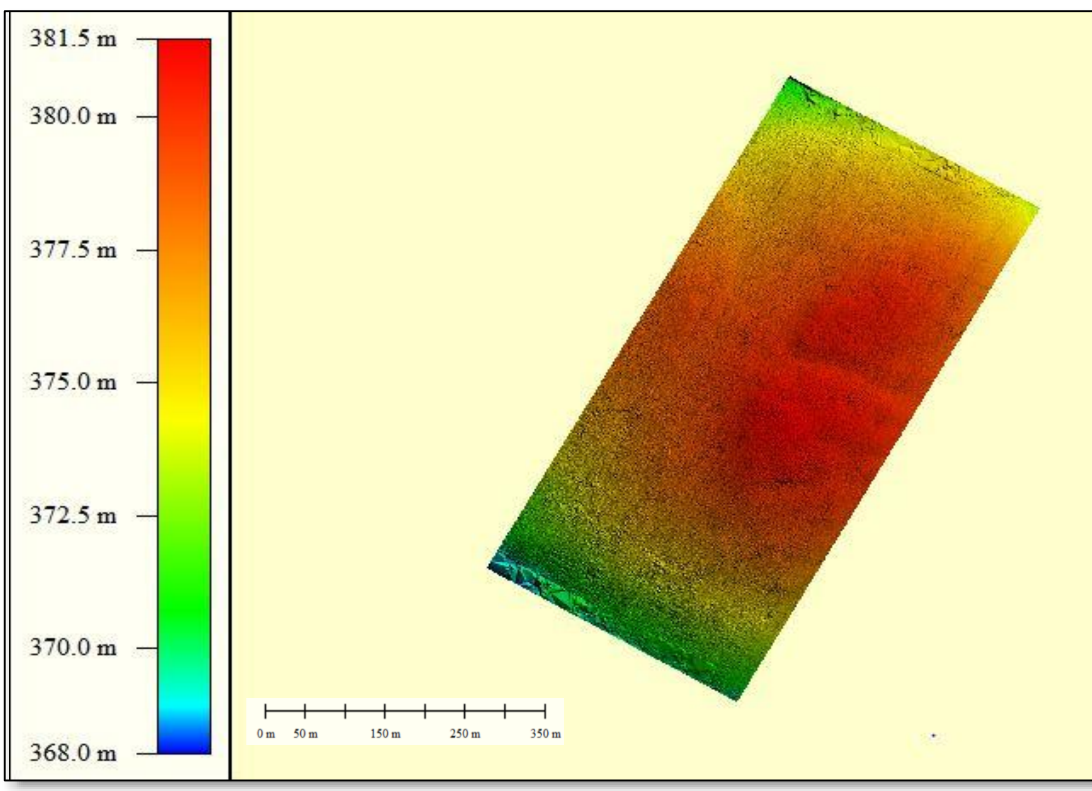


Figure 24: The Digital Terrain Model

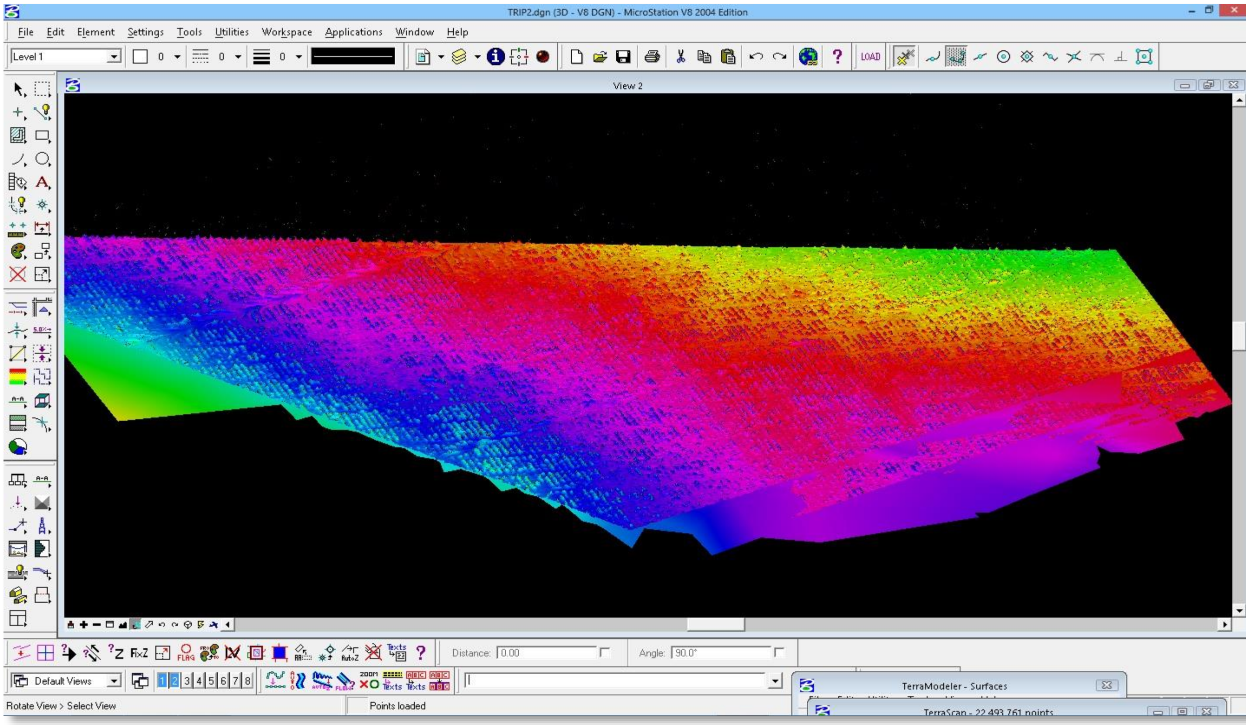


Figure 25: Crop Surface Model- Jun

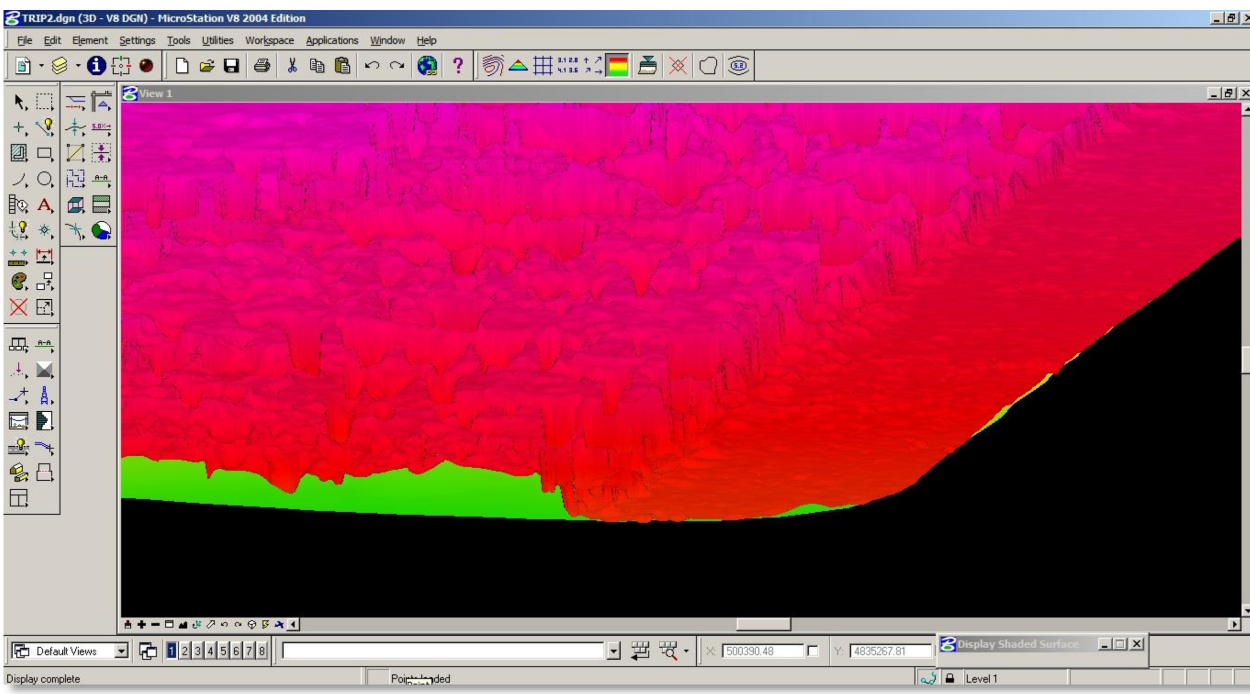


Figure 26: Crop Surface Model- September

Further processing was carried out in Microstation V8. The CSM was clipped which form the area of interest (AOI). To account for boundary effects, the plots were reduced by 0.3 m on each end, and the areas were destructive biomass sampling was performed were excluded. In the next step, the CSM is subtracted from the ground model to obtain the PH. The mean PH was calculated for each plot and used for the biomass estimation with a regression model. This process is repeated for the CSM of each date.

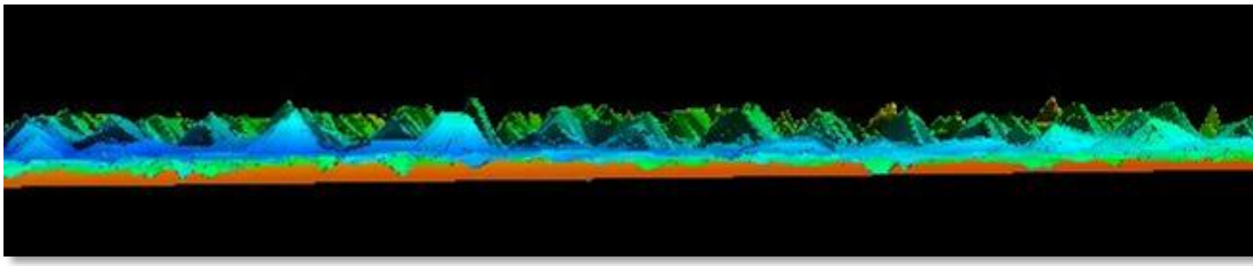


Figure 27: 3D view Crop Surface Model

Minus Tool was run in ArcGIS to determine the Plant Height and the height of the plant ranged from 5.6 to 8.4 meters.

6.3 Weed Detection:

Weed detection is carried out by determining the height or profile of anomalies across plots. Crops are generally of uniform heights, so sudden dips or peaks in the profile denote the potential presence of weeds.

The only way to spot weeds is to visually inspect if they are present. For farmers who own large fields, this is time consuming–and time is an expensive commodity. The use of a UAV allows for the quick and frequent visualization of fields and consequent analysis through anomaly detection to immediately identify areas where weeds are prevalent.

This addresses the problem by:

(1) Immediately identifying weeded areas and

(2) Allowing the farmer to act in a targeted manner.

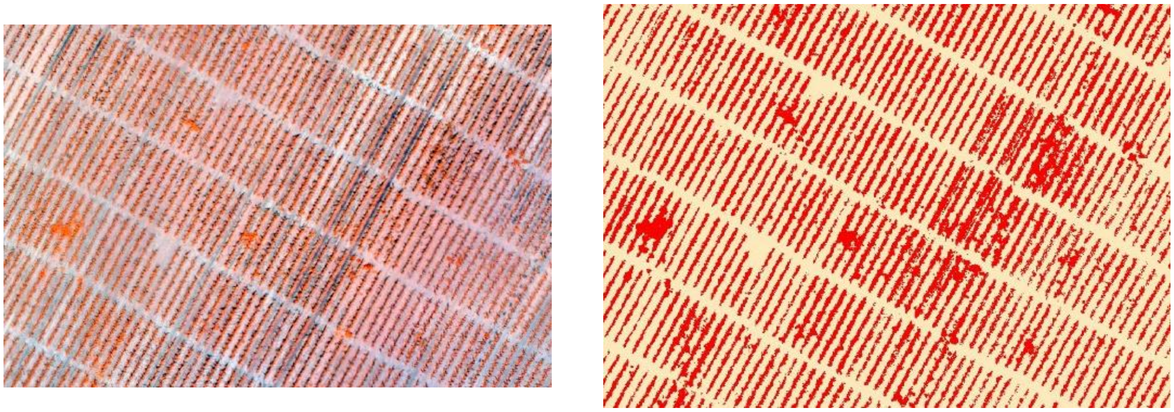


Figure 28: Visual Inspection of Weeds

The peaks or the anomalies in the above cross section of the Digital Surface Model denote the presence of weeds. This helps farmers to take appropriate actions to prevent its further growth.

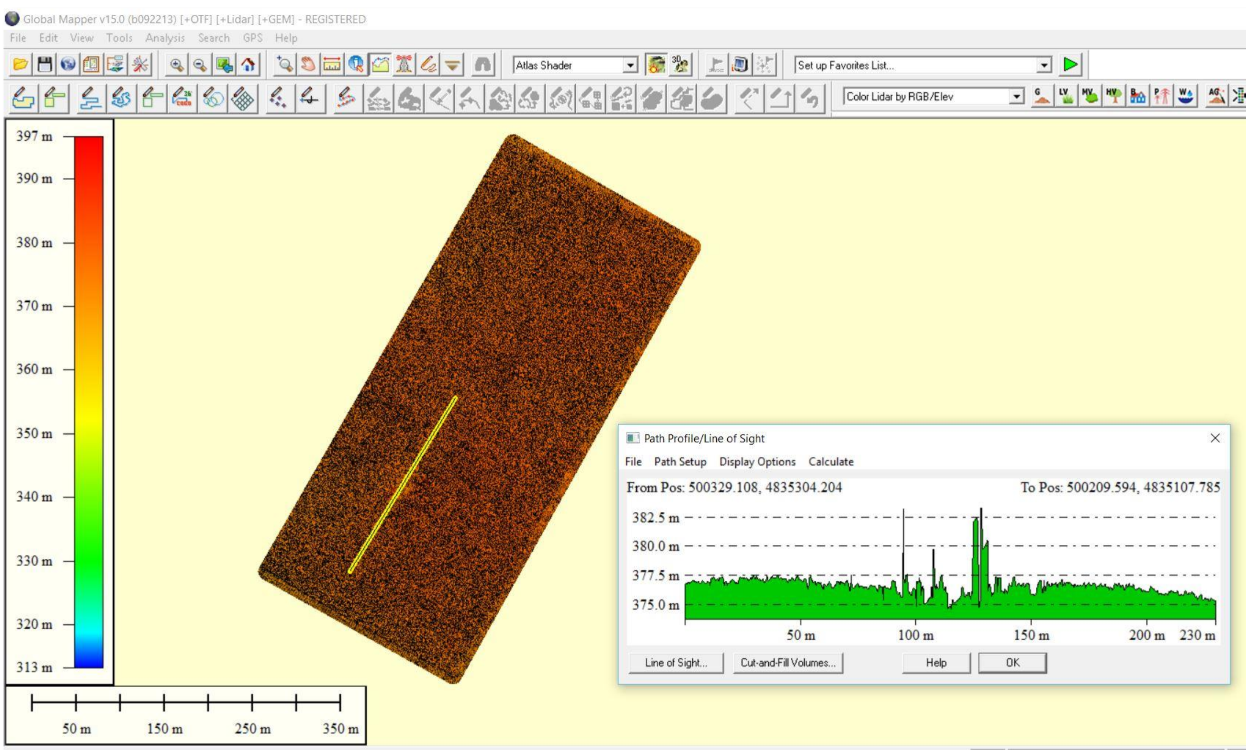


Figure 29: Cross Profile denoting the presence of weeds

6.4 Vegetation Indices

Vegetation indices (VIs) are developed to qualitatively and quantitatively evaluate vegetation using spectral measurements in relation to agronomic parameters like biomass (Bannari et al., 1995). Presently, site-specific crop management (SSCM), an important component of precision agriculture is being pursued vigorously to increase production.

6.4.1 Enhanced Normalised Difference Vegetation Index:

ENDVI differs from the earlier NDVI calculations as it uses blue/green visible light instead of the red-only method. This allows for better isolation of plant health indicators and produces a False Colour Mapping to indicate the value of Vegetation Index at that pixel.

ENDVI includes a comparison of Green light in addition to NIR, Red, and Blue in order to give a more sensitive result. This isolates the indicators of plant health, and can be used to assess the presence and health of a crop.

$$\boldsymbol{ENDVI} = \frac{(NIR + Green) - 2 * Blue}{(NIR + Green) + 2 * Blue}$$

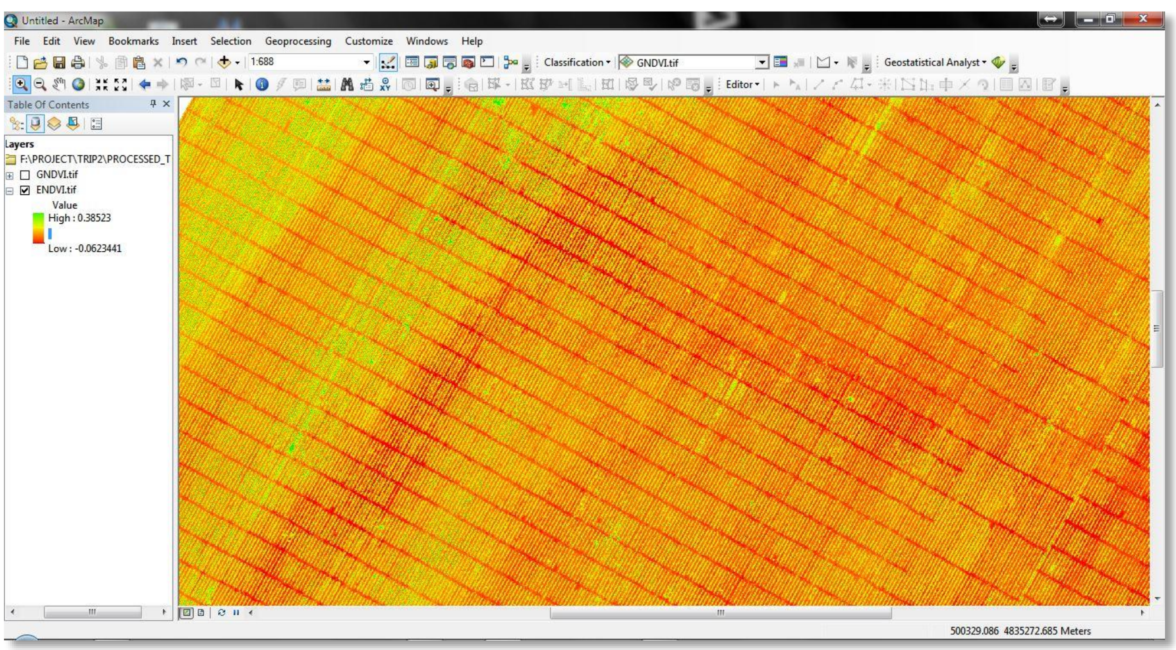


Figure 30: ENDVI - June, 2015

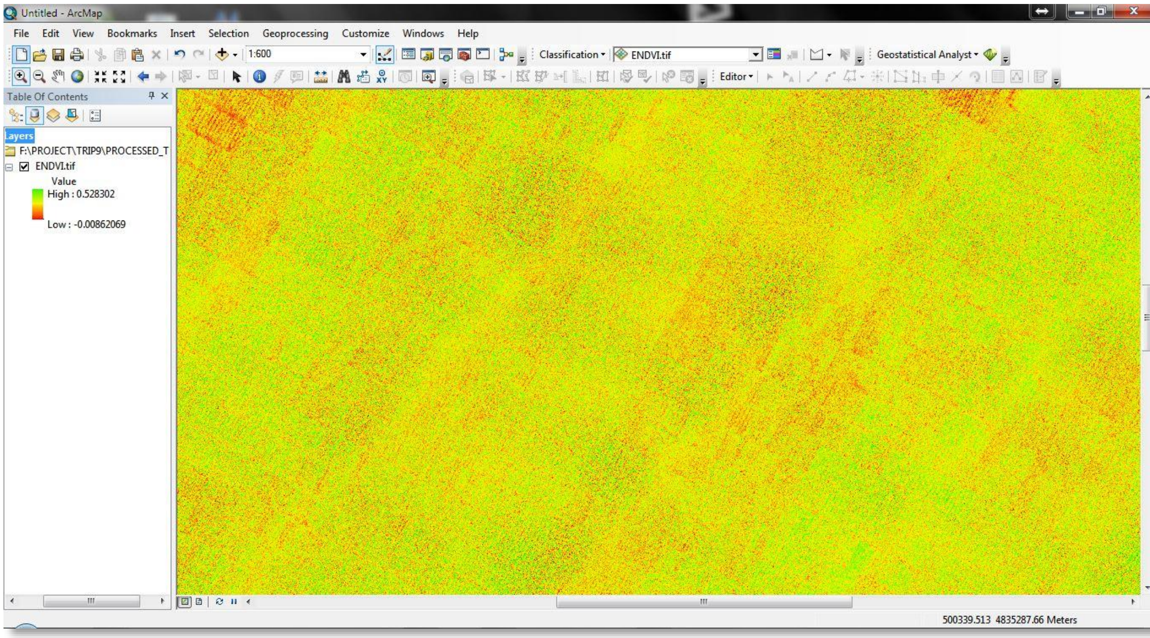


Figure 31: ENDVI - September, 2015

ENDVI was estimated on the images captured on June and September, which acted as a strong indicator of plant health as seen from the higher index value of 0.52 in September as compared to the value of 0.38 in the month of June.

6.4.2 Green Normalised Difference Vegetation Index:

This index is similar to NDVI except that it measures the green spectrum from 540 to 570 nm instead of the red spectrum. This index is more sensitive to chlorophyll concentration than NDVI.

$$\boldsymbol{GNDVI} = \frac{(NIR - Green)}{(NIR + Green)}$$

From the images below, the abundance of chlorophyll content in September image is clearly visible as compared to the June image. This index is an excellent indicator of the plant growth and its health status. The index value increases to 509 from a value of 154 in June.

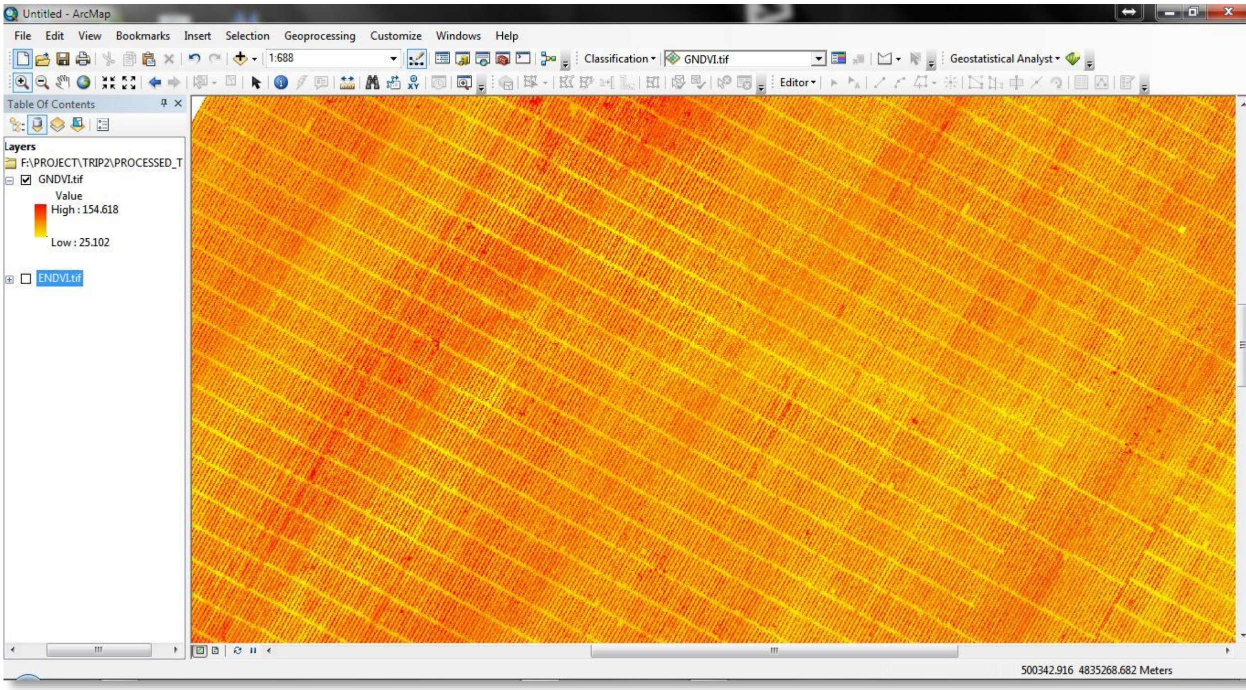


Figure 32: GNDVI- June, 2015

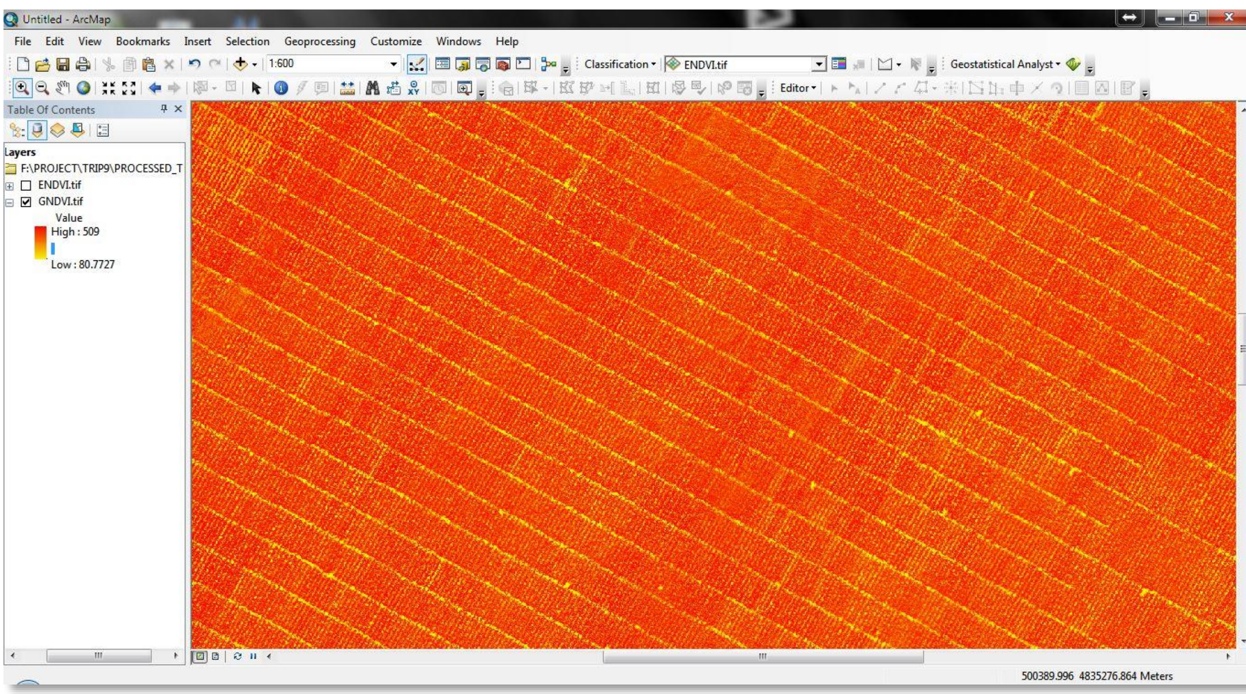


Figure 33: GNDVI: September, 2015

6.5 Field Health Report

The plot-level zonal statistics of the September, 2015 was computed since this month was found to be the yield peak month. The vegetation indices ENDVI and GNDVI act as an excellent indicator of the plant health and vigour. The study area was broken down into 5*5 m grids and the maximum, minimum, mean and standard deviation for each plot was computed.

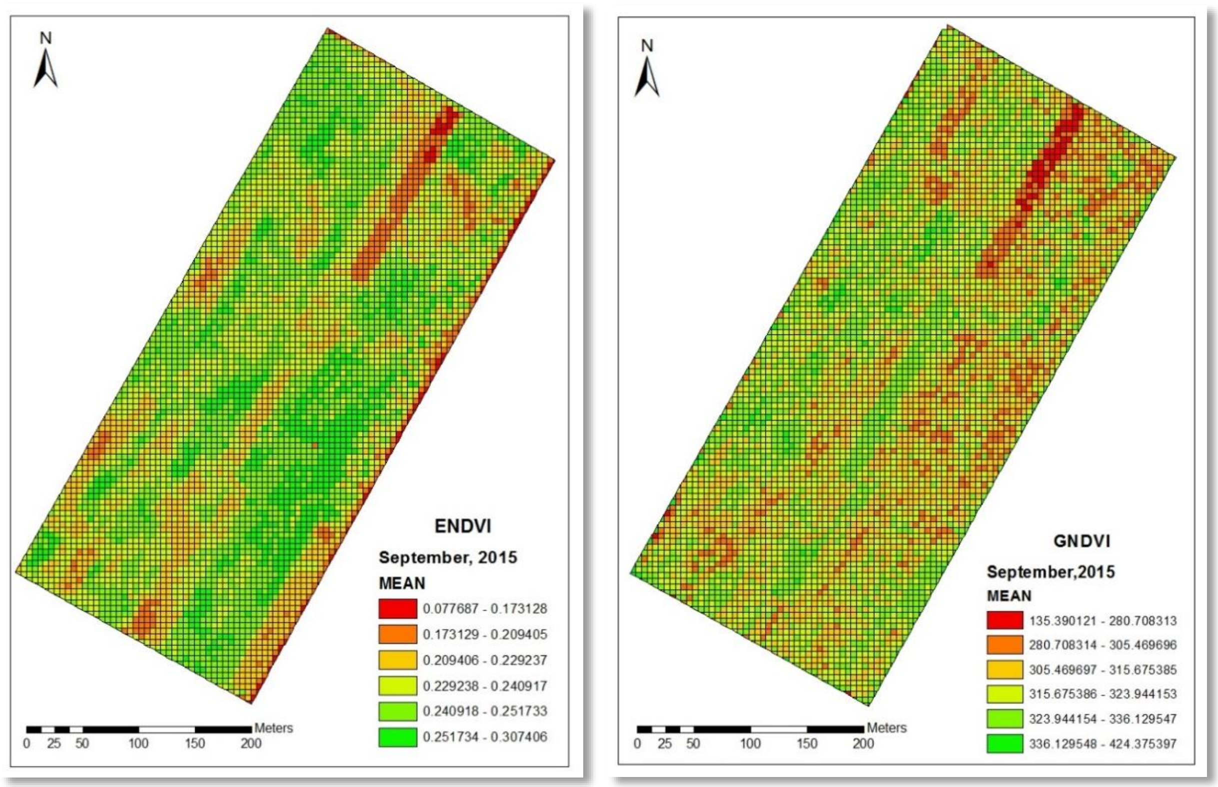


Figure 34: Field Health Status based on Indices

From the above maps one can clearly determine the areas which requires immediate attention. Computing both the indices helped us to further distinguish between the healthy and unhealthy crop conditions.

Whole field, in-season current condition data is considered to be a valuable piece of information in a precision program. This field health reports distinguish healthy areas from those that require attention, thus enabling farmers to see where to make timely adjustments during the growing season. The report helps in identifying areas compromised by hailstorms, blights, insects and other pests in time to treat those areas and increase yields or to deprioritize them for the season.

6.6. Correlating Indices with In-situ Yield Values:

The purpose of this study was to show that a model can be constructed based on GNDVI and ENDVI that would allow us to predict corn yield using the multi-spectral images from our aerial survey. This would be a result similar to the data that has been acquired in-situ corn yield. The yields and average GNDVI scores from 12 locations in the field of the survey area are taken for the purpose of generating a correlation.

Serial No.	*Yield (in Bushels)*	*ENDVI*	*GNDVI*
1	0.1688	0.25100	156.692
2	0.2027	0.31120	315.583
3	0.1677	0.24555	174.694
4	0.0576	0.16522	344.513
5	0.1388	0.23894	139.739
6	0.1148	0.19041	396.431
7	0.1368	0.22602	376.504
8	0.1235	0.23129	361.460
9	0.1988	0.32948	229.686
10	0.1767	0.25127	370.528
11	0.1496	0.23435	133.660
12	0.1221	0.22222	373.504

Table 5: The In-situ Yield and the Indices Value for the 12 sample locations

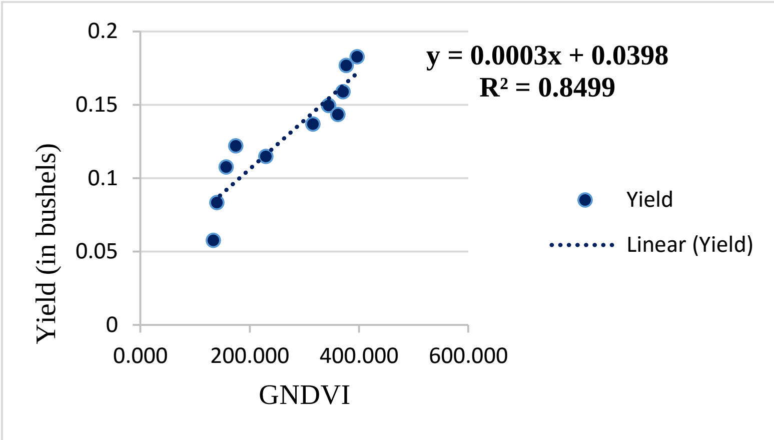


Figure 35: Correlation between In-situ yield and GNDVI Values

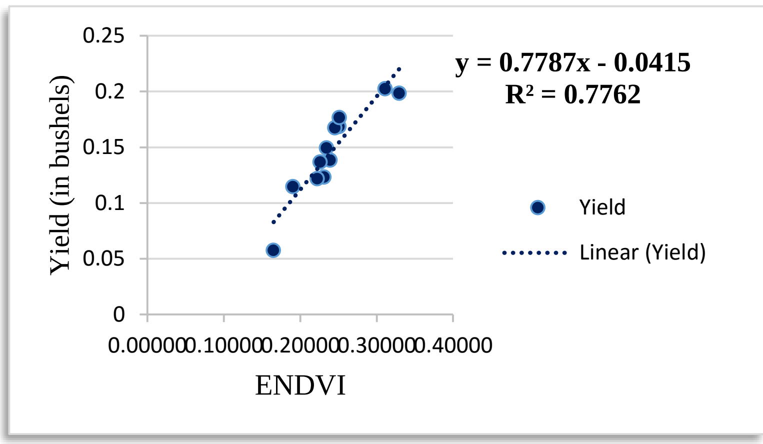


Figure 36: Correlation between In-situ yield and ENDVI values

The results from the correlation can be used to make a predictive model of yield based on the average GNDVI and ENDVI score. By fitting a logarithmic curve to the data as shown in Figure we create a yield model where the coefficient of determination was found to be 0.7762 and 0.8499.

Therefore a strong positive relationship was established between the sample yield data collected on the field and the indices computed.

6.7 Yield Estimation

Biomass as a productivity parameter of crop can be used as an effective tool for forecasting yield capacity. We can obtain area distribution of this parameter using aerial data or satellite measurements. Obtained data of biomass can be used as an input parameter in crop growth model and also directly used for forecasting the yield capacity of field, taking into account correlation between crop yield and biomass.

Assessing the dry matter amount from standing biomass on fields is methodologically difficult, as it involves manual sampling and measuring the total biomass as well as the dry matter content. In addition most fields show spatial heterogeneity of their growth conditions and thus varying yield levels within fields.

Crop biomass can be estimated with different techniques. Reflectance measurements base on the instantaneous relationship between spectral reflectance and biomass (Baret et al., 1989). VIs are derived from reflectance data and thus VIs are suitable for crop biomass estimation. Several studies demonstrate the relationship of different vegetation indices (VIs) and biomass on various spatial scales (Gitelson et al., 2003; Heiskanen, 2006; Le Maire et al., 2008).

The yield of the crop was estimated using the correlation found out between the sample in-situ yield data and the GNDVI Index. GNDVI was chosen since it had a higher positive regression value of 0.8499. Using the equation of the straight line i.e. $y = 0.0003x + 0.0398$, a yield map was prepared and the zonal statistics of the same 8 locations were computed to show that difference between the actual yield and the computed figures.

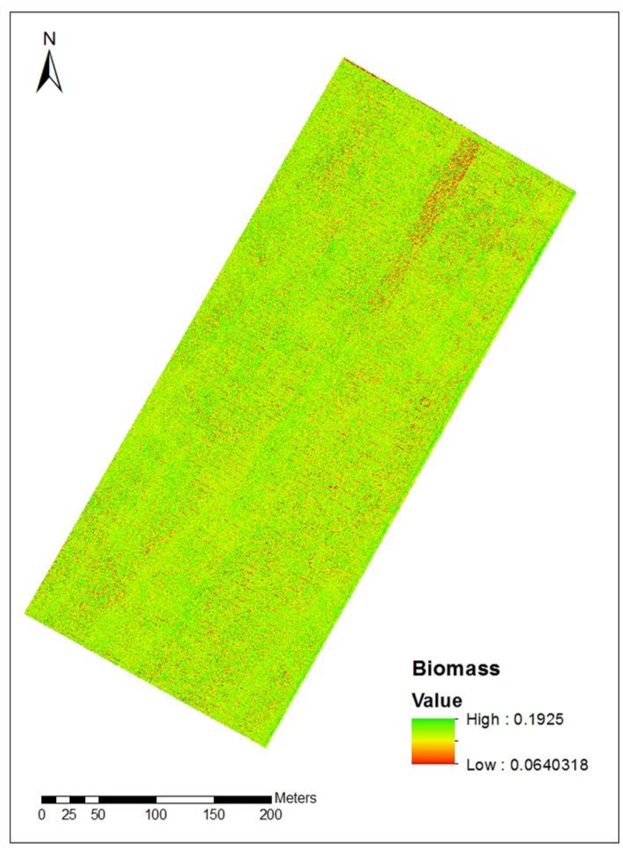


Figure 37: Yield Estimated Map

Serial No.	Estimated Yield Values (in Bushels)	In-Situ Yield Data (in Bushels)
1	0.0868075	0.1088
2	0.1344750	0.1227
3	0.0922082	0.1677
4	0.1431540	0.1576
5	0.0817216	0.1388
6	0.1587290	0.1148
7	0.1527510	0.1368
8	0.1482380	0.1235
9	0.1087060	0.1188
10	0.1509580	0.1767
11	0.0798980	0.1096
12	0.1518510	0.1221

Table 6: Comparison between In-situ Yield Data and Estimated Yield Data

From the above table it can be seen there is a slight difference from the actual in-situ yield data and the values computed from the study. Therefore this can be used as an effective way to determine the crop yield rather than using the traditional crop cutting experiment techniques

6.8 Comparison with Conventional Technology

The conventional technology used for yield estimation is generally through Crop Cutting Experiments. The major loopholes in the technique are:

- One or more plots are chosen as samples from commercial fields.
- Not possible to estimate the yield in an individual field with acceptable statistical precision.
- At times, Eye estimates of yield per acre are made for many fields and a random subsample of fields for crop cutting is taken.

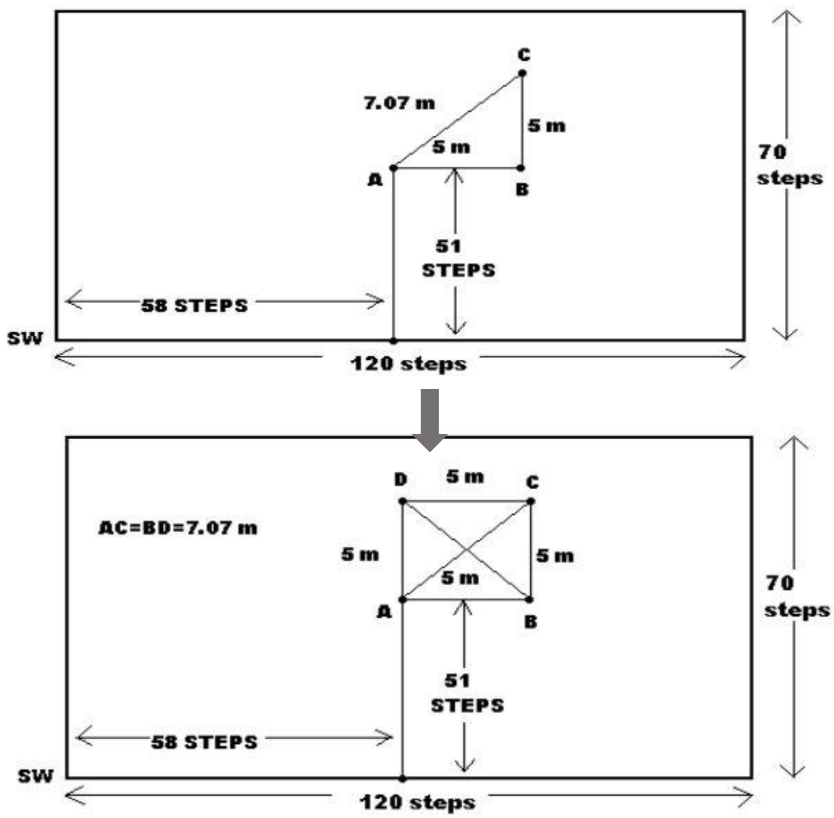


Figure 38: Selection of Plots for Crop Cutting Experiments

Yield Estimation through remote sensing has a major advantage. It saves time. When yield of a much larger area can be generated using the various vegetation indices and a few sample in-situ data, the tedious field work carried out for estimating the yield can be avoided. Moreover, inconsistency of the data can also be prevented.

6.9 Crop Insurance Computation:

For, the purpose of the study, we have chosen the most commonly used technique. Multiple Peril Crop Insurance (MPCI) is a broadbased crop insurance program. Crops eligible for MPCI coverage in Iowa include corn, soybeans, oats, wheat, seed corn, popcorn, barley, potatoes, sweet corn, canning beans, dry beans, forages, grain sorghum, green peas, tomatoes, and nursery stocks. There are two decisions that determine the amount of protection obtained from MPCI:

- the level of yield coverage chosen
- the level of price coverage chosen

Indemnity Payments: If your actual average yield (adjusted for quality) is equal to or greater than the yield guarantee, no indemnity is paid. If the average yield per acre is less that the yield guarantee, the indemnity paid is equal to the yield difference times the indemnity price, times the number of acres insured.

Actual Production History yield is computed as a simple average of from four to ten consecutive years of actual yields based on your production records. If you cannot prove four consecutive years of yields, “T yields” will be substituted for the missing years. The T yields vary by county, and are equal to the most recent 10-year county average yield. If only one year of the four is missing, the T yield is used for the missing year. However, if two or more years are missing, you can use only a percentage of the T yield, as shown below.

- 1 year missing - use 100 percent of T yield
- 2 years missing - use 90 percent of T yield
- 3 years missing - use 80 percent of T yield
- 4 years missing - use 65 percent of T yield

So, The APH for Perth County was computed from its past 10-year yield data and the observation were as follows:

Year	Yield(Bushel/ Acre)
2011	160.5
2012	166.4
2013	165.6
2014	--
T Yield	**155.1363636**

Table 7: Yield Values of Perth County for 3 consecutive years

Year	Yield(Bushel/ Acre)
2011	160.5
2012	166.4
2013	165.6
2014	(T Yield*100)155
APH	**161.875**

Table 8: Computation of APH

Based on the APH the farmers could insure its crops. The insurance yield is based on your actual production history (APH), which is an estimate of your average yield on the insured unit for four to ten consecutive years. One can insure its crop at from 50 to 85 percent of your APH yield, in increments of 5 percent. The yield guarantee per acre is equal to your APH insurance yield multiplied by the level of coverage one chooses**.**

This method however faces a major limitation. The yield is calculated as an average for the entire county rather than individual fields. Therefore, with the help of remotely sensed data and the outputs generated from this study can help insurance companies to decide the exact amount of insurance that should be provided to the farmers for their own plot of land since the yield values are likely to vary from farm to farm. By monitoring a crop throughout its growing season, insurance companies can also avoid a lot of faulty payments by identifying the anomalies and weeds during the growing season itself. They can suggest corrective measures than can be used by farmers for a perfect healthy crop growth.

7. Conclusion

There is much ado about the potential for applications of UAVs to take precision agriculture to the next level. The economic value of UAVs to agriculture has been broadly touted with little basis for the estimates. UAVs have been particularly important for crop monitoring during the early part of the growing season, when cloud cover may prevent satellite data acquisition. Using the UAV data, the yield of the crops can be precisely determined which could help farmers and policy makers in taking appropriate decisions. Moreover, it has also been found out that it significantly a better method than the conventional crop cutting experiment technique.

Therefore, to conclude crop insurance is a major prospect where UAV data can be utilized. Studies have found out more than 50% of a farmer's yield gap is due to weather conditions. There are a number of ways that drones are predicted to enhance efficiency of initial insurance surveys, from basic visual damage assessment to increased operational tempo. After the study concluded, there was two main findings:

1. Drones provide estimated yield increase

Assumption: Current crop yields are not achieving their maximum potential. Yield is, on average, about 20% less than it could be under optimal circumstance.

Finding: Study estimates that drones can reduce the management yield gap by up to 25%

2. Drones provide input savings

Assumption: Farmers tend to over-apply resources

Finding: Drones provide information that enhances variable rate technology, reducing input cost. Study estimates there is a 5% additional input saving by using the information collected by a drone.

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Appendix

Year	Area Seeded (acres)	Area Harvested (acres)	Yield(bushels/acre)
2004	104,900	104,900	127
2005	97,500	95,800	158
2006	108,765	105,800	161
2007	150,000	146,800	145
2008	100,000	99,300	156
2009	110,000	109,000	139
2010	115,000	113,700	170
2011	126,591	121,421	160.5
2012	114,567	104,857	166.4
2013	118,356	116,990	165.6
2014	95,949	94,900	158.0

Table 2: Yield Values of Perth County, Ontario, Canada

Annexure

THE HINDU

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http://www.thehindu.com/todays-paper/tp-national/drones-to-help-gauge-crop-damage/article7727876.ece

Drones to help gauge crop damage

The Centre has decided to use satellite and drones (unmanned aerial vehicles) over farmers' fields to collect crop yield data and to assess damage from natural calamities.

The high resolution imagery of crop assessment from drones will be collated with satellite imaging and other geospatial technology to get accurate data to enable crop insurance companies to give proper compensation to affected farmers. The experiment will help develop index-based data for insurance companies.

Launching the new programme called "Kisan" (Crop Insurance using Space Technology and Geoinformatics), Minister of State for Agriculture Sanjeev Balyan told journalists on Monday that the scientific data collected by drones and collated with satellites imagery will be matched with traditional crop cutting experiments to arrive at a foolproof data. Among the drone companies active in India are SkyMet, Amigo Optima, Precision Hawk, Quidich and Techbaaz.

"The crop insurance claim is calculated on the basis of crop cutting experiments. However, there has always been a problem in getting timely and accurate data, due to which payment of claims to farmers were getting delayed. A new programme "Kisan'' is being launched on a pilot basis to address this issue,'' Mr. Balyan said.

At the same time, the Minister launched an Android mobile phone application to assess large-scale damage to crops from hail. Farmers with Android and smart phones will download the application which will allow them to immediately send photos of their crop damage to officials concerned for immediate relief. This will cut the red tape in reaching assistance to farmers, the Minister said.

Initially, "Kisan'' will be tried out as a pilot study in identified districts in Haryana, Karnataka, Maharashtra and Madhya Pradesh. Studies will be done during the ongoing kharif season in rice crop in Kurukshetra (Haryana), Shimoga (Karnaraka), Seoni (Madhya Pradesh) and in cotton in Yavatmal (Maharashtra).

Next rabi, pilot studies will be carried out in wheat yields in Hissar and Karnal (Haryana), Ahmednagar (Maharashtra) and Vidisha and Hoshangabad (Madhya Pradesh). Studies will be done in sorghum in Gulbarga (Karnataka) and Solapur (Maharashtra) and in rice in Raichur (Karnataka).

The programme will be jointly conducted by Mahalanobis National Crop Forecast Centre, Indian Space Research Organisation, India Meteorological Department, State Agriculture Departments and Remote Sensing Centres, Climate Change, Agriculture and Food Security (CCAFS).