EVALUATION OF REMOTE SENSING VEGETATION INDICES FOR MONITORING MAIZE CROP CONDITION AND YIELDS IN TANZANIA

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ABSTRACT

Monitoring smallholder production systems for crop condition and yield through remote sensing techniques is challenging due to the heterogeneity of farming systems. The study was conducted at Sokoine University of Agriculture (SUA) and Magadu farmers' maize fields in Morogoro Tanzania. This study investigated the relation between vegetation indices (VIs) and field measurements of crop condition and yield as indicated by maize growth (biophysical) parameters under mixed farming practices. Unmanned Aerial Vehicle (UAV) and Landsat 8 (green, red, red-edge, and near infrared spectral bands) were used to calculate four spectral vegetation indices; the normalized difference vegetation index (NDVI), wide dynamic range vegetation index (WDRVI), red-edge chlorophyll index ($CI_{red\text{-}edge}$), and the green chlorophyll index (CI_{green}). The CI_{green}, $CI_{red\text{-}edge}$ and NDVI showed ability to detect differences in maize crop biophysical parameters with CI_{green} and NDVI performing better than the other indices. The CI_{green} and NDVI were the best indices for detection of the effect of fertilizer application (fertilizer and non-fertilizer) and pigeon pea intercropping (with pigeon pea and without pigeon pea intercrop) on maize at 60 days after sowing due to $R^2 > 0.50$. The best performance of these indices was on grain yield, where all UAV-VIs detected yield variability by higher R^2 values (> 0.60) for both sole and intercropped maize. The assessment for the usefulness of satellite remote sensing VIs showed that the satellite derived VIs were significantly affected more by cloud cover than UAV-VIs. Thus, the NDVI and WDRVI derived from UAV and Landsat 8 were significantly different ($p < 0.05$); unlike UAV-CI_{green} which exhibited some consistence with Landsat 8-CI_{green} and their differences were not statistically significant except under heavy cloud cover. These findings clearly demonstrate the need to use multiple vegetation indices to best monitor maize crop conditions and yield differences attributed to different farming practices and weather conditions.

DECLARATION

I, ISACK B. YONAH do hereby declare to the Senate of Sokoine University of Agriculture that this dissertation is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

13/2/2017.

ISACK B. YONAH **DATE**

The above declaration is confirmed

14/02/2017

PROF BONIFACE P. MBILINYI **DATE**

13/02/2017

PROF SIZA D. TUMBO **DATE**

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This work is dedicated to my father Mr. Isaya Baliyendeza, mom Agnes, and brother Marton who laid the foundation of my education.

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LIST OF ABBREVIATIONS

CCIAM	Climate Change Impact Adaptation and Mitigation
DAS	Days After Sowing
GIS	Geographical Information System
IIPM	Illinois Integrated Pest Management
MAFC	Ministry of Agriculture Food Security and Cooperatives
RS	Remote Sensing
SPSS	Statistical Package for Social Sciences
STARS	Spurring a Transformation for Agriculture through Remote Sensing
SUA	Sokoine University of Agriculture
TMA	Tanzania Meteorological Agency
UAVs	Unmanned Aerial Vehicles
USA	United States of America
USDA	United States Department of Agriculture
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VIs	Vegetation Indices
WMO	World Meteorological Organization
WRS	Worldwide Reference System

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background information

Decisions on food security needs during the season have been misjudged in the past due to a lack of information on condition of crops and pastures, seasonal outlooks, access to markets and likely production levels. STARS (2015) reports on situations where crop produce imported erroneously before what turned out to be a bumper crop led to an oversupply of food and financial difficulties for smallholder farmers as food prices plummeted. Tanzania has the second largest area of approximately 4.12 million hectares in 2012 planted to maize in Africa after Nigeria (Abate *et al.*, 2014). Planted area and crop yield estimates are based on conventional methods (CMs) of data collection on crops that involve field visits and reports which is expensive, labor-intensive and data delivery often leads to significant delays (Dempewolf *et al.*, 2015) and may contain errors.

The use of remote sensing (RS) to monitor and estimate maize yields by vegetation indices (VIs) is being explored in some countries, for examples in Africa; Zimbabwe (Svotwa *et al.*, 2014), South Africa (Frost *et al.*, 2013), West Africa (Forkuor *et al.*, 2013). With the use of remote sensing technology, plant physiological and morphological differences can be distinguished within fields in real time, cost efficiently and timely. Time series of VIs can help in the development of region specific phenologies for multiple crop types while limiting the necessity of intensive field monitoring (Wang *et al.*, 2016).

The technology and use of remote sensing imagery from satellite and Unmanned Aerial Vehicles (UAVs) has rapidly advanced but the application of these technologies for agricultural monitoring in subsistence agricultural areas have been limited. Also, monitoring smallholder production systems through existing remote sensing techniques is highly challenged by: the substantial heterogeneity in crops, soils, farm practices, and climatic conditions; the often small and ill-defined farm plots, holding multiple crops and undergoing variable types of crop management. The heterogeneity of farming system due to ill-defined plots, variation in planting dates, and mixed cropping has been reported to have effect on vegetation index due to mixed pixels or pixel contamination (Guindin-Garcia, 2010).

In spite of various RS derived VIs in use due to their ease of computation yet they vary in their sensitivity to crop canopies (Viña *et al.,* 2011) and lack ability to capture yield differences between fields (Sibley *et al.*, 2014). On the other hand, conventional remote sensing methods for monitoring crop condition use coarse spatial and temporal resolution RS products, for example Landsat (30 m resolution) which is too infrequent to capture many of the rapid biological and meteorological changes while Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m resolution is too coarse for small and mixed cropping fields.

Although the degree of optimism towards the potential contribution of RS to agriculture monitoring and yield estimation is justifiable with argument, but little is known on the effect of mixed farming system on VIs and ability of VIs to detect yield differences between fields. Also, the VI-based approaches are often not sufficient due to the fact that they often rely only on one parameter (the observed VI) and do not consider the persistence of the stress period (Balint *et al., 2011*). Water stress is one of the most important factors limiting growth, metabolism, yield and evapotranspiration in plant. Crop water stress index (CWSI) derived from canopy and air temperature is a good indicator of water stress in crops (Ünlü *et al.*, 2011).

Therefore, this study aims to deploy field measurements of maize growth parameters; number of leaves per plant, plant height, crop stage, green leaf area index (LAI), biomass and grain yields, and crop water stress index (CWSI) for evaluation of a few selected VIs potential for monitoring maize condition and yield under different farming practices of fertilizer application and pigeonpea intercropping farming practices. This work has evaluated four remote sensing derived VIs; the normalized difference vegetation index (NDVI); wide dynamic range vegetation index (WDRVI); and red edge chlorophyll index ($CI_{red\text{-}edge}$) and green chlorophyll index (CI_{green}) derived from unmanned aerial vehicle (UAV) fine resolution imagery and coarse resolution satellite products obtained from Landsat 8 sensors.

1.2 Objectives

1.2.1 Overall Objective

The overall objective of the study was to evaluate the most recent VIs for their potential applicability for monitoring maize conditions and yields under mixed farming practices and fertilizer application, thus offering for more effective evidence-based information useful to agriculture and agricultural policy makers.

1.2.2 Specific Objectives

The specific objectives were to;

i. Determine important plant parameters for evaluation of vegetation indices derived from fine and coarse RS data
ii. Determine important vegetation indices derived from UAV data for their variation under mixed farming conditions
iii. Determine the relationship between crop parameters and VIs derived from fine resolution UAV data

iv. Assess the usefulness of coarse resolution satellite images for monitoring maize crop condition and yields

1.3 Hypothesis

It was hypothesized that;

i. There is no relationship between vegetation indices and the changes in ground measured plant condition parameters relevant for maize yield.

ii. There is no difference between vegetation Indices (VIs) derived from maize crop under mixed cropping and fertilizer application.

iii. There is no difference between remotely sensed parameters derived from satellite (coarse resolution) and UAV (fine resolution) data, thus any can be used as tool potential for monitoring maize growth and yield under farmer's field conditions.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Crop biophysical parameters

2.1.1 Plant height and number of leaves

Plant height and number of leaves per plant have been related to yield, competitiveness and water stress tolerance ability. Smaller and less leafy plant has lower level of competition over the others; under water limited environment the lower amount of vegetative biomass reduce water cost per plant for vegetative growth and maintenance, resulting in greater resource availability for grain production (Sangoi and Salvador, 1997). Maize plant height has been reported to be a potential parameter for characterising spatial variation of plant to inputs and field conditions (Shrestha *et al.*, 2002). Their findings revealed the potential of using stereo vision for crop height measurements, although estimated plant heights were poorly correlated in the case of large plants due to overlapped leaves. Plant height is a key indicator of plant growth linked to Nitrogen nutrition during vegetative development of maize, and its measurements at vegetative stages 10 and 12 can be used to predict maize yield (Yin *et al.*, 2011). The study, however used only one maize cultivar (Pioneer 33N58) thus demand for more test across different maize cultivars.

2.1.2 Leaf area index, biomass and grain yield

Leaf area index (LAI) and biomass are important crop condition characteristics used for estimation of primary production and forecasting crop yield (Rundquist *et al.*, 2014; Kim *et al.*, 2012). LAI is important in explaining the ability of the crop to intercept solar energy for biomass production and in understanding the impact of crop management practices (Kim *et al.*, 2012). LAI estimates in space and time from remotely sensed vegetation indices (VI) contribute to improve yield forecast. Citing Watson (1947), Kim *et al.* (2015) indicated that LAI was defined as the ratio of leaf area to a given unit of land area, a ratio that is functionally linked to spectral reflectance. Spectral reflectance is used to derive spectral vegetation indices which are the mathematical combinations of different spectral bands mostly in the visible and near infrared regions of the electromagnetic spectrum (Viña *et al.*, 2011).

2.1.3 Crop Water Stress Index (CWSI)

It has been found that canopy temperature is usually lower than air temperature under sufficient soil water conditions with the basic assumption that transpiration cools the leaves and as available soil moisture decreases, transpiration is reduced and therefore the temperature of leaves increases. For monitoring vegetation stress a single VI-based approaches are often not sufficient due to the fact that they often rely only on one parameter (the observed VI) and do not consider the persistence of the stress period (Balint *et al.*, 2011).

2.2 Vegetation condition indices

Vegetation index is an indicator describing the greenness, the relative density and health of vegetation in each pixel of remote sensed image (USGS, 2015). The leaf reflectance changes in response to leaf thickness, species, canopy shape, leaf age, nutrient status, and water status, thus it has led to the development of various spectral vegetation indices (VIs) (Gitelson, 2011). Time series of vegetation indices can help in the development of region specific phenologies for multiple crop types (Wang *et al.*, 2016).

2.2.1 Normalized difference vegetation index

Normalized Difference Vegetation Index (NDVI) is calculated as a ratio between the red (R) and near infrared (NIR) values (Rouse *et al.*, 1974) as shown in Eq. 1:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad \text{.......} (1)$$

NDVI can reveal where vegetation is thriving and where it is under stress, as well as changes in vegetation due changes in plants' phenological phase (USGS, 2015). It's the most-used spectral index derived from remote sensing imagery for assessing crop condition of major crops and forecasting crop yield, though it saturates in very dense and vigorous (healthy, green) canopies (Dempewolf *et al.*, 2013). It is the best index for detecting changes in maize green LAI < 3 m^2 m^{-2} (Guindin-Garcia, 2010), thus limit its ability to quantify LAI late in the growing season (Wang *et al.*, 2016).

2.2.2 Wide dynamic range vegetation index

The wide dynamic range vegetation index (WDRVI) is the modification of NDVI that uses the same bands as the NDVI, with the advantage of describing a wide range of vegetation cover before becoming saturated (Gitelson, 2004). WDRVI can be obtained from NDVI (Eq. 2);

$$WDRVI = \frac{\alpha.\rho_{NIR} - \rho_{Red}}{\alpha.\rho_{NIR} + \rho_{Red}} \quad \text{.......} (2)$$

Where, weighting coefficient ($\alpha = 0.2$) is introduced to attenuate the contribution of the NIR region at moderate-to-high green biomass, and to make it comparable to that of the red region (Guindin-Garcia, 2010). High WDRVI values are observed at the peak of the season (Sibley *et al.*, 2014), it is more sensitive at high values common in maize canopies (Gitelson, 2004); enables a more robust characterization of crop physiological and phenological characteristics (Viña *et al.*, 2011). WDRVI and Chlorophyll indices have the lowest errors in estimating green LAI and have shown to be the most accurate VIs for LAI estimation in maize, soybean, wheat, and potato (Nguy-Robertson *et al.*, 2015).

2.2.3 Red-edge chlorophyll index

The red edge chlorophyll index ($CI_{red\text{-}edge}$) has been used in estimation of chlorophyll content and green colour separation of green leaves in maize (Nguy-Robertson *et al.*, 2015). $CI_{red\text{-}edge}$ is a crop type insensitive which may not require re-parameterization under different crop types, thus a suitable, accurate and yet inexpensive tool for the remote estimation of Green LAI at multiple scales (Viña *et al.*, 2011). Gitelson *et al.* (2005) describes $CI_{red\text{-}edge}$ as shown (Eq. 3);

$$CIred - edge = \frac{\rho NIR}{\rho Red - edge} - 1 \quad (3)$$

Where ρNIR the spectral value in the Near Infrared window and $\rho Red - edge$ is for red edge window. Filella and Penuelas (1994) highlights on the variation of red-edge spectral band with chlorophyll content of the plant. As chlorophyll content of the plant increases the red edge peak moves to longer wavelengths because its absorption band becomes broader. Red-edge band is not generally available to low-cost multispectral sensors (Viña *et al.*, 2011; Boegh *et al.*, 2013), making it important for use with high resolution sensors in precision agriculture.

2.2.4 Green chlorophyll index

Green reflectance ($\rho Green$) was found sensitive to canopy scale chlorophyll variation than ρRed due to data saturation in the peak absorption bands of chlorophyll caused by strong absorption of red light by the bulk chlorophyll content (Yoder and Waring 1994; Gitelson *et al.*, 1996) as cited by Boegh *et al.* (2013). Thus, the green chlorophyll index (CI_{green}) was proposed to measure the total canopy chlorophyll content (Gitelson *et al.*, 2005) (see Eq. 4).

$$CIgreen = \frac{\rho NIR}{\rho Green} - 1 \quad (4)$$

2.3 Remote sensing for monitoring crop condition and yield

Crop biophysical parameters have been used to evaluate remote sensing VIs for their potential to monitoring crop conditions and yields. There have been efforts to quantify the relationship between VIs and crop biophysical characteristics (Gitelson, 2004, 2011; Guindin-Garcia, 2010; Hartfield and Prueger, 2010; Viña *et al.*, 2011). Their studies tried to quantify VIs with agricultural crop (maize inclusive) characteristics at different growth stages under varying management practices. Their results show that the VIs have been used to quantify various agronomic parameters such as leaf area index, crop cover, biomass, crop type, nutrient status, and yield (Gitelson, 2011); fertilizer application recommendations (Blaes *et al.*, 2016; Boegh *et al.*, 2013), and chlorophyll contents based on canopy reflectance measurements (Frost *et al.*, 2013). Constructing time series of vegetation indices from satellite imagery can help in the development of region specific phenologies for multiple crop types (Wang *et al.*, 2016). New approaches have been proposed using regions of the light spectrum that do not show saturation to different concentrations of pigments and green biomass such as red-edge and green regions (Buschman and Nagel, 1993; Gitelson *et al.*, 1996; Gitelson *et al.*, 2003) as cited by Guindin-Garcia (2010). The CIred-edge and CI_{green} were identified among the 12 indices tested by Gitelson (2015) as best performers for estimating the gross primary productivity in maize and soybean. Though these indices have been developed there have been limited efforts to evaluate their capability to detect changes in crop conditions and yield differences under mixed cropping and fertilizer application in Tanzania.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Description of study area

3.1.1 Location, climate and soils

The study was carried out at the crop museum (for experimental plots) located within main campus of Sokoine University of Agriculture (SUA) Morogoro Tanzania (Latitude 6.83°S and Longitude 35.65°E) and farmers' maize fields located at Magadu, about 2 km from the experimental site (Figure 1). The total average annual rainfall ranges between 820 mm to 1,500 mm, with the highest mean temperature of about 33°C occurring between November and December. The soil is acidic, less fertile due to its low nitrogen, low phosphorus and marginal organic carbon content in the top soil (Mourice *et al.*, 2014). Location of the study areas is shown in Figure 1.

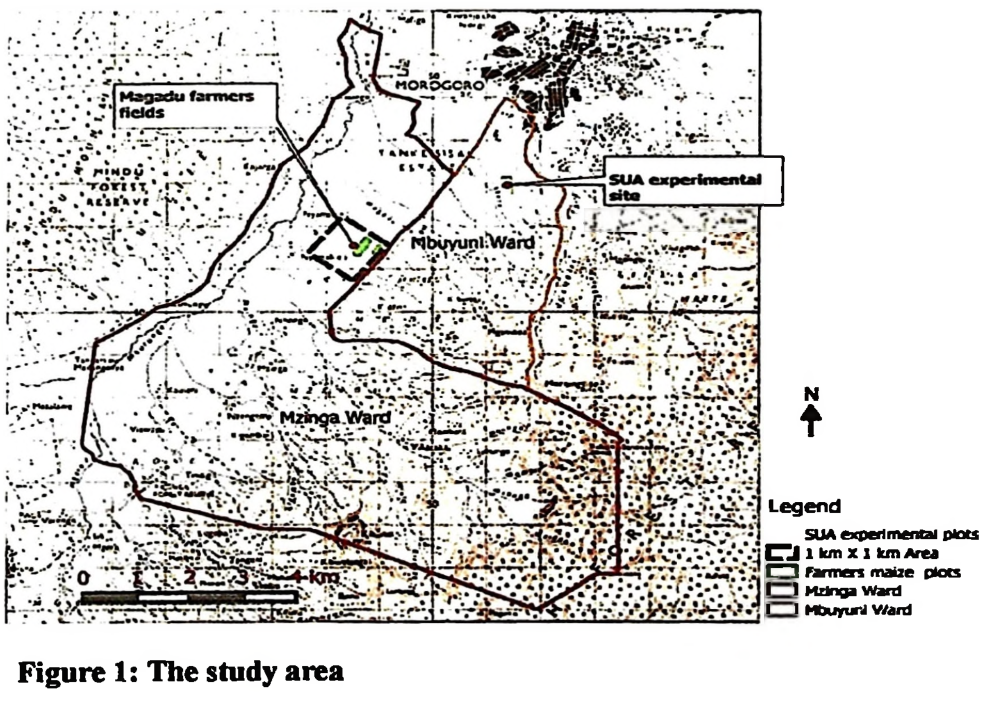

Figure 1: The study area

3.1.2 Weather conditions for March – May 2016

Data on rainfall, evaporation and sunshine hours were collected from Tanzania Meteorological Agency Morogoro office located within 500 m radius from the experimental site. Rainfall was measured by standard rain gauge and evaporation by standard evaporation pan both for 24 hours and in millimeters (mm). The sunshine was measured by using sunshine cards in minutes. The data was used to describe the season and possible implication on crop and soil moisture conditions averaged over a 10 – day (dekadal) interval.

3.2 Experimental design and treatments

3.2.1 SUA experimental plots

The study deployed a 2 × 2 × 2 multifactor-factorial layout with randomized block design that considers three factors with maize crop as an experimental variable having two treatments (varieties) and two control variables (fertilizer and maize-pigeon pea intercropping), each one having two levels. The design contained a total of eight cells as shown in Table 1. For successful implementation of this design, a total of 24 farm plots of 5 m x 10 m size were established into 3 replications of 8 plots each (Figure 2). Each plot represented treatment combination randomly allocated in each replication as indicated in Figure 2. Maize (*Zea mays L.*) and pigeon pea (*Cajanus cajan*) were grown as maize mono crop at 30 cm x 75 cm spacing and maize-pigeon pea intercrop (inter-row) during March – May 2016 rainfall season. The crops were well-watered using seasonal rainfall supplemented with irrigation, carefully maintaining a crop.

Two maize varieties *Pannar* 3M-01 and *Situka* 2 were used in this study. *Pannar* 3M-01 (variety PEX 4405) is an early maturing maize variety which matures in 3-3.5 months, characterized by good husk cover, good standing ability, flint, tolerant to leaf diseases and it is meant for 900-1400 m above mean sea level (Migwi, 2015). *Situka 2* is characterized by plant height: 1.84-2.10 m; leaf orientation: $45\text{-}60^{0}$; days to 50% flowering: 45-55 days and days to 50% silking: 78 days (MAFC, 2008). Di-Ammonium Phosphate (DAP 18-46) fertilizer was applied at sowing followed by NPK (23-10-5) forty days after sowing according to the treatment layout (Figure 2). Both fertilizers were applied at 5g/hill. The ground sampling areas of 3 m x 3 m were identified for the 24 plots of which each sampling point represented any main visible variations in crop appearance and account for local variations resulting from fairly homogenous crop composition and treatments.

Table 1: A 2x2x2 multifactor-factorial design Modified after C.R. Kothari, 1990

		Experimental variable			
		***Situka* maize variety**		***Pannar* 3M-01 maize variety**	
Control variables		**Variable 2:** Pigeonpea intercropping		**Variable 2:** Pigeonpea intercropping	
		Level I No	**Level II** Yes	**Level I** No	**Level II** Yes
Control variable 1:	**Level I** No	Cell 1	Cell 3	Cell 5	Cell 7
Fertilizer	**Level II** YES	Cell 2	Cell 4	Cell 6	Cell 8

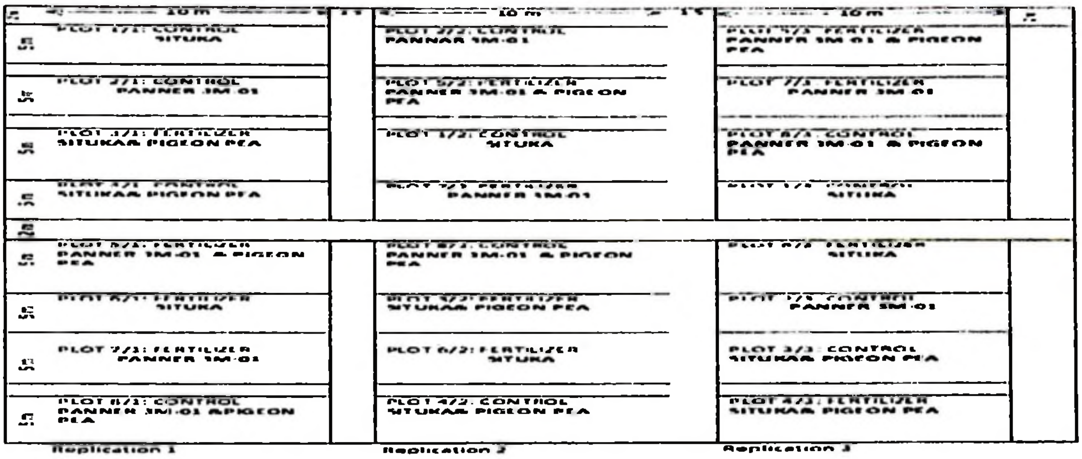

Figure 2: Experimental layout showing treatment combination randomly allocated into three replications.

3.2.2 Farmers' maize fields

Two maize fields were selected to assess the usefulness of satellite images for monitoring maize condition and yield at farmer's field condition (Figure 3). The fields were located within 1 km x 1 km area in Magadu village about 3 km from the SUA experimental site. They were one of the fields under STARS crop monitoring project during March-May 2016 main cropping season. Field 1 was about 425 m x 100 m with identified six plots of 70 m x 100 m size. The field was chosen because it was well managed and had defined plots planted on 10 March 2016 with *Pannar* 4M19 locally known as *Mkombozi*, except in one plot where SIDCO maize variety was grown (Figure 3). Field 2 was planted during first rains in mid- February, and it contained variable crop stages and management. Crop growth stage, crop management and condition, and UAV imageries were collected after every 16 days to match with the temporal resolution of Landsat 8 images. To cover an area of 1 km x 1 km, Multispec4c and S110 RGB cameras were mounted on UAV-eBeefly, with multispec4c camera flown at height of 192 m (lateral overlap 60%, longitudinal overlap 75%, and ground resolution 0.02 m/pixel) and RGB flown at 143.1 m (lateral overlap 50%, longitudinal overlap 90%, and ground resolution 0.05 m/pixel). Seven UAV and Landsat 8 images were collected between March and June 2016.

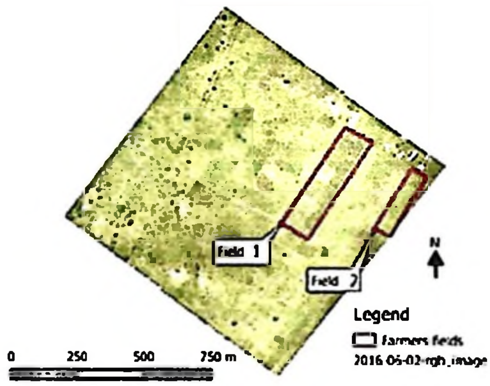

Figure 3: Farmers maize fields (Field 1 and 2) located in 1 km x 1 km.

3.3 Materials for field data collection

Field data was collected for biophysical parameters which included plant height, LAI, CWSI (canopy temperature, dry and wet bulb temperatures), biomass, and grain yield. The remote sensing data included UAV and Landsat 8 images. Figure 4 shows some of the equipment used for field data collection. UAV field data collection equipment was (1) computer, (2) eBeefly, (3) multSPEC4c camera, (4) multiSPEC 4c camera calibration board, and (5) RGB camera. Equipment for crop biophysical parameters measurements were; (6) collapsible ruler (plant height), (7) Infra-Red thermometer (canopy temperature), (8) Psychrometer (wet and dry bulb temperatures), and (9) Smart phone equipped with PocketLAI software (LAI). Measurement of biomass and grain yield was by using (spring) and electrical balances (not shown). Measurements and use of those equipment are described in details in sections 3.4 and 3.5.

Figure 4: Materials for field data collection

3.4 Measurement of crop biophysical parameters

Maize height, average number of fully developed leaves, crop development stage, and CWSI were measured 30 days after sowing for comparison purposes with LAI (Soria-Ruiz *et al.*, 2004). Biomass and grain yield were measured after physiological maturity. Plant development stage followed the *Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie* (BBCH) scale of phenological stages (Earth Observation Research Branch Team, Agriculture and Agri-Food Canada, 2012). The development stages for maize according to BBCH scale are: (1) leaf development (from 10 to 19) covering period from first leaf through coleoptile to 9 or more leaves unfolded; (2) stem elongation (from 30 to 39)- beginning of stem elongation to 9 or more nodes detectable; (3) inflorescence emergence, heading (from 51 to 59)- beginning of tassel emergence, tassel detectable at top of the stem to end of tassel emergence when tassels are fully emerged and separated; (4) flowering, anthesis (from 61 to 69)- stamens in in middle of the tassel visible and tip of ear emerging from leaf sheath to end of flowering when stigma completely dry; (6) development of fruit (from 71 to 79) – beginning of grain development when kernel is at blister stage about 16% dry matter to a period when all kernels have reached final size; (7) ripening (from 83 to 89) – early dough kernel content soft at 45%

dry matter to fully ripe when kernels are hard and shiny, 65% dry matter; and (8) senescence (from 97 to 99) - plant died and collapsing to harvest product.

3.4.1 Plant height and number of leaves per plant

Plant height was measured using a ruler held upright from soil surface to top leaf (flag) canopy following the method described in IIMP (2006). Measurements were done between 9:00 and 10:00 am when the leaves are still upright as indicated in Figure 5. Five plants were randomly selected from two middle rows, consistently monitored and their heights were averaged per plot. Number of leaves per plant was determined by counting a number of fully developed leaves identified by visible leaf collars. Following Abedroth (2011) cited by Nielsen (2014), counting of leaves on maize plant begins with the lowermost, short, rounded-tip true leaf and ending with the uppermost leaf with a visible leaf collar. Leaf collar is the light-colored collar-like "band" located at the base of an exposed leaf blade, near the spot where the leaf blade comes in contact with the stem of the plant.

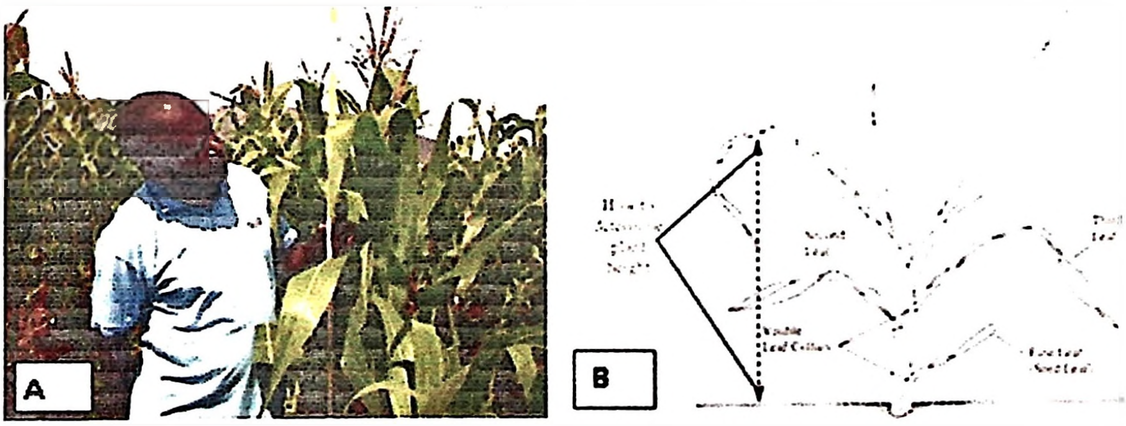

Figure 5: Author (left) taking plant height measurements using collapsible ruler at SUA experimental plots (A), and (B) Illustration to plant height measurement.

3.4.2 Leaf Area Index (LAI)

Non-destructive measurement of LAI was performed early in the morning, when there was more diffuse and less direct solar radiation, using PocketLAI smart phone application (Confalonieri *et al.*, 2014). The LAI measurements were done by holding the smartphone under the maize canopy and slowly move the camera from horizontal to vertical whereby the images are automatically captured by the device at an ideal angle of 57.5° following the second vibration (Figure 6). After the second vibration, the application collects five LAIs and computes average LAI value. The LAI was measured along the same row of maize plants within a 2 m x 2 m area.

Figure 6: Author measuring LAI using smartphone equipped with PocketLAI software at SUA experimental plots.

3.4.3 Crop Water Stress Index (CWSI)

Crop Water Stress Index (CWSI) was computed as follows:

$$CWSI = (Tc - Tw) / (Td - Tw) \quad (5)$$

Where; Tc is the canopy temperature; Tw is the wet bulb temperature (temperature of a leaf transpiring at the maximum potential rate); Td is the dry bulb air temperature (the temperature of a non-transpiring leaf). Tc measurements were taken within 2 m x 2 m area around each field plot using a handheld infrared thermometer (IRT) AMPROBE model IR-712 set at emissivity, α = 0.98 and average temperature (AVG). The measurements were taken as integrative measurements, scoring the entire canopy of many plants within rows in a plot and IR thermometer up and down 3 times across the plant canopy. Tw and Td were recorded using a manual aspirated psychrometer - Psychron 15691. Temperature measurements were done after every four days to be able to capture changes within the eight day interval matching with remote sensing observation window. Both canopy and air temperatures were recorded concurrently between 14:00 and 15:00 h after solar noon when plant water deficit has been maximized (López- López *et al.*, 2011). This time window is recommended for once-a-day data acquisition if the goal is to capture maximum stress level (Taghvaeian *et al.*, 2013). If Tc equals Tw the CWSI is 0 and there is no water stress. If Tc equals Td the water stress of the plant is at its maximum.

3.4.4 Maize biomass and grain yield

A harvest area of 3 m x 3 m was established in each plot and method by Verhulst *et al.* (2013) was used for biomass and yield estimation. To determine biomass, 10 maize plants post physiological maturity (sampling date 12 July 2016, 125 DAS) were selected randomly outside harvest area, and were cut at 10 cm from the ground, ears were carefully removed but leaving the husks with the plants. Total fresh weight of the 10 plants without ears was determined. Five plants were randomly selected from 10 plants and chopped, from which about 1 kg of this chopped materials was placed to paper bag to form a sub-sample which was weighed and placed in oven at 75 ^{0}C for 48 hours until constant dry weight. The ears were placed in the paper bags and dried in the oven at 75 ^{0}C for 48 hours until they have a constant dry weight. Ears were threshed and weight of dry grain was determined.

For estimation of grain yield, all ears in the harvest area were harvested (sampling date 19 July 2016, 132 DAS) dried on sun and weighed before threshing. Grains weight without cobs was recorded as total grain weight from which a subsample of about 200 g was weighed and recorded as fresh weight before oven drying at 75^{0}C for 48 hours to constant dry weight. After 48 hours, 200 unbroken kernels were counted as they come without looking for better looking ones and were oven dried at 75 ^{0}C for 24 hours and determine a 200 grains dry weight (Verhulst *et al.*, 2013). The following formulas were used for determination of biomass and grain yield (Verhulst *et al.*, 2013) as shown in Eq.6 - 9.

$$\text{Biomass yield (kg/ha)} = \frac{\text{Dry yield}}{\text{Harvest index}} * 100 \quad (6)$$

$$\text{Dry yield (kg/ha)} = \frac{\text{Total grain yield} - \text{Moisture content}}{\text{Harvest Area}} * 10 \quad (7)$$

$$\text{Harvest index (HI)} = \frac{\text{Dry weight grain}}{\text{Total Biomass 10 plants}} * 100 \quad (8)$$

$$\text{Moisture content (g)} = \text{Total grain weight} \times \text{Per cent moisture} \quad (9)$$

The summarized Tables for final biomass and grain yields are included in Appendices (–5).

3.5 Acquisition and pre-processing of remotely sensed images

3.5.1 UAV images

Unmanned Aerial Vehicle (UAV) images were collected using multiSPEC4c Airinov and RGB Canon S110 cameras fitted on eBee drone. The Multi SPEC4c Airinov camera offers four spectral bands (green 550 nm, red 660 nm, red edge 735 nm. and near infrared-NIR 790 nm). The flight plan was prepared using eMotion 2 software package which allows a user to interact with eBee. The flight plan was based on the size of the field and surrounding features which determine the flying altitude and the amount of overlaps required and ultimately affect ground resolution (Table 2).

Calibration was done for multiSPEC4c Airinov camera using calibration board where calibration images are taken before flight. The flight interval was 8 days for SUA experimental area and 16 days for Magadu farmer's fields. The intervals allowed for describing crop development within the UAV and Landsat image acquisition windows. To minimize the effects of shadows, the eBee was flown between 10:00 h and 12:00 h noon or after mid-day between 13:00 h and 14:00 h (Taghvaeian *et al.*, 2013) when image acquisition dates for both sites coincided. Images were processed using eMotion and Postflight-Terra3D software following procedures highlighted in the eBee user manual (SenseFly, 2014).

Image processing started with eMotion where all raw images and three calibration images were imported into the software and by using information stored in the flight log file, the project.p4d was created when the importation is finished. The Postflight-Terra3D software was used to process the p4d project to generate green, red, red-edge and NIR mosaic images group required for computation of vegetation indices or mosaic group for visual display of the field condition as shown by RGB sample images at SUA experimental site (Figure 7). Appendix 6 shows the data and work flow involved in image processing and analysis.

Table 2 Type of camera and characteristic features

Characteristic features	Camera	
	MultiSPEC4C_3.6	RGB Canon S110
(a) SUA experimental plots		
Image size	1280 x 960	4000x3000
Ground sampling distance	0.12 m/pixel	0.04 m/pixel
Lateral /longitudinal overlap	50/90%	50/90%
Spectral bands	Green, red, red-edge, and NIR	Green, blue and red
Sensor Dimensions	0.0048 m x 0.003600 m	0.00744 m x 0.005580 m
Altitude	96 m	96 m
Calibration	Required	Not required
(b) Magadu farmer's fields		
Image size	1280 x 960	4000x3000
Ground sampling distance	0.2 m/pixel	0.0684 m/pixel
Lateral /longitudinal overlap	50/90%	50/90%
Spectral bands	Green, Red, Red-edge, and NIR	Blue, Green and Red
Sensor Dimensions	0.0048 m x 0.003600 m	0.00744 m x 0.005580 m
Altitude	192 m	143.1 m
Calibration	Required	Not required

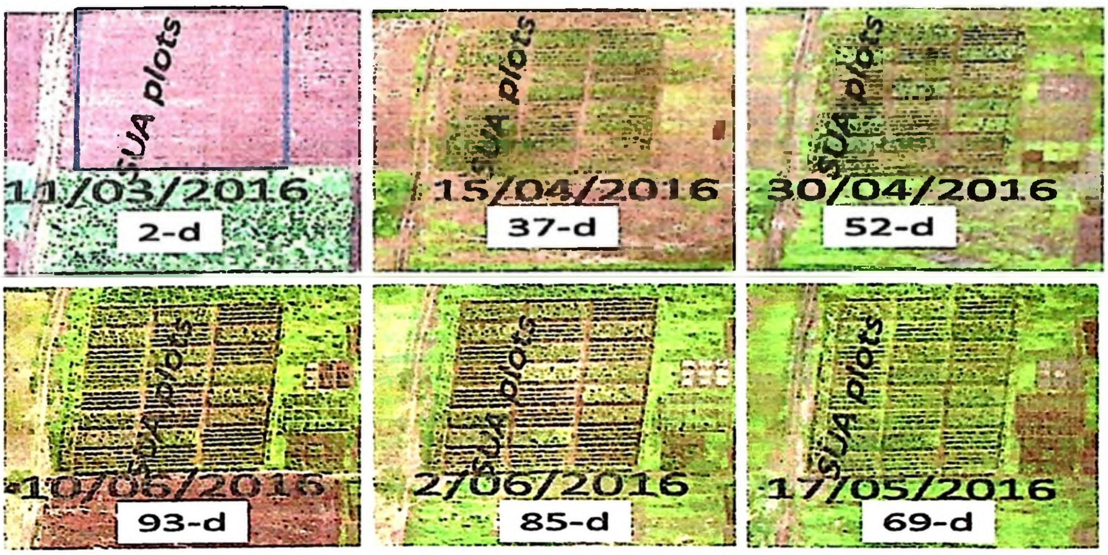

Figure 7: SUA experimental field plots indicating field condition over 24 plots against date and number of days after sowing.

3.5.2 Landsat-8 images

Landsat 8 (Operational Land Imager-OLI) images (Path 167 and Row 65) at 30 m and 16-day spatial and temporal resolution, respectively, were downloaded from the USGS Global Visualization Viewer (http://glovis.usgs.gov/index.shtml). Landsat 8 consists of 11 bands, where band 3 (green 0.53 - 0.59), band 4 (Red 0.64 - 0.67 μm), and band 5 (NIR 0.85-0.88 μm) are used for derivation of vegetation indices; NDVI (Rouse *et al.*, 1974); WDRVI (Gitelson, 2004); CI_{green} and $CI_{red\text{-}edge}$ (Gitelson *et al.*, 2005). Band 3 (green) emphasizes peak vegetation, which is useful for assessing plant vigor; band 4 (red) discriminates vegetation slopes, and band 5 (NIR) emphasizes biomass content and shorelines. The Quantum Geographic Information System (QGIS) was used for image pre-processing, including layer staking, re-projection, and image sub-setting. Staked images were re-projected to WGS84 UTM zone 37 south. Image subsetting and enhancement was done to improve image interpretability and to provide better input for other automated image processing procedures (Usha *et al.*, 2012).

3.6 Determination of plant parameters for evaluation of vegetation indices

Plant parameters (LAI, plant height, crop development stage, average fully developed leaves, final biomass and grain yield were determined and plotted against dates and days after sowing (DAS) and compared their variations for monocrop maize and intercropped maize-pigeon pea under fertilizer or no fertilizer application conditions. The period (s) of clear differentiation among maize biophysical parameters were identified from time series graphs. LAI, plant height, crop development stage, number of leaves per plant were determined and averaged for the periods of parameter differentiation windows identified by clear divergent lines or peak depicted by DAS on a time series graph.

Gradient analysis on time series graph was carried out to identify period (s) when there was clear differentiation within (same) variety or between (different) varieties. Vertical interval was the difference between two values corresponding with biophysical parameter observed at two DAS. Horizontal interval is the difference between two DAS values (Eq. 10).

$$\text{Biophysical gradient (V)} = \frac{V(t2)-V(t1)}{DAS(t2)-DAS(t1)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

Where;

DAS (t1) and DAS (t2) are the number of days after sowing for two different dates (t1) and (t2). The V(t1) and V(t2) are the biophysical parameter values observed at DAS (t1) and DAS (t2). DAS (t2) is greater than DAS (t1).

Biomass and grain yield were determined for each treatment combination at the end of the season. Biomass and grain yield were converted to an area of one hectare, with grain adjusted to standard moisture content of 12.0 % (Shitumbanuma, 2013; Verhulst *et al.*, 2013). These crop biophysical parameters were summarized using GenStat statistical software (Buysse *et al.*, 2007) and the means which were then tested using t-test to find out if the departures observed at parameter differentiation windows were statistically significant at 5% probability level.

3.7 Determination of the vegetation indices derived from UAV and Landsat images

Vegetation indices were determined for SUA experimental plots and two farmers' maize fields. QGIS software was used for statistical computation of vegetation indices raster calculator plugin following the formula; $NDVI = (\rho_{NIR} - \rho_{Red})/(\rho_{NIR} + \rho_{Red})$ (Rouse *et al.*, 1974); $WDRVI = (0.2*\rho_{NIR} - \rho_{Red})/(0.2*\rho_{NIR} + \rho_{Red})$ (Gitelson, 2004); $CI_{red\ edge} = (\rho_{NIR}/\rho_{Red}) - 1$ and $CI_{green} = (\rho_{NIR}/\rho_{Green}) - 1$ (Gitelson *et al.*, 2005). The VIs raster images for both UAV and Landsat 8 images were obtained. To obtain the descriptive statistics for VIs for each farm plot, shape files of rectangular polygon(s) were created (Figure 8). For SUA experimental field a shape file with 24 rectangular polygons of 4.5 m x 9.5 m each was created to cover each treatment plot for the three replications as shown in Figure 8 (A). Similarly, at farmer's field conditions, six (70 m x 100 m each) and three (about 45 m x 50 m each) polygons were created for Field 1 and Field 2 respectively as seen in Figure 8 (A and B).

Figure 8: (A) SUA experimental field; column represents replication and numbers represent treatment combinations. (B) Farmers' maize fields (Field 1 and Field 2) and seven sampling plots.

The RasterStats plugin available in QGIS was used to generate the average vegetation indices for the area enclosed by each rectangle in each raster image. The mean VIs for Field 1 and Field 2 for each observation date was the average of the six and the three plots respectively.

3.8 Data exploration

Descriptive statistics was used to explore data, identify oddities and generate summaries before detailed data analysis. It utilizes numerical and graphical methods to look for patterns in a data set to summarize the information revealed in a data set, and to present that information in a convenient form (McClave and Sincich, 2004). Descriptive statistics and boxplots are typically used for data exploration to describe or summarize the data, examine the variables of interest, potentially before conducting inferential statistics on them. The following variables were examined for univariate outliers: Plant height, number of leaves per plant, LAI, CWSI, NDVI, WDRVI, CIred-edge, and CIgreen. Z-scores greater than 3 absolute (McClave and Sincich, 2004) are considered outlier, but this study has classifies data scores outside the range of ± 3.29 standard deviations from the mean as univariate outliers.

3.9 Determination of relationship among and between crop parameters and VIs

Prior to analysis, the data was subjected to statistical test to assess their normality. The Shapiro-Wilk test provided by the GenStat software was used to assess the normality. Shapiro-Wilk test is based on the correlation between the data and the corresponding normal scores (Peat and Barton, 2005) and it's highly recommended for small sample sizes of less than 50 (Elliott and Woodward, 2007), and provides better power than the Kolmogorov-Smirnov (K-S) test even after the Lilliefors correction (Steinskog, 2007; Ghasemi and Zahedias, 2012).

Data collected on crop parameters from 24 plots were averaged and Shapiro Wilk test statistic (W) for normality was conducted in GenStat. Results presented in Table 3 indicate that parametric statistics should be used for all parameters except CI_{green} ($W = 0.8937$, $p = 0.016$) where non parametric statistics should be used (Ghasemi and Zahedias, 2012). Pearson correlation was used for parameters that depicted normal distribution ($p > 0.05$) otherwise Spearman's rank correlation was used for parameters not normally distributed ($p < 0.05$). Two sided t-test was used to test the strength of correlation coefficients (r) if significantly different from zero (Buysse *et al.*, 2007; WMO, 2011). Coefficient of determination (R-squares, R^2) was computed from r. R- Squared has been used as measure of the performance of vegetation indices (Dempewolf *et al.*, 2013; Blaes *et al.*, 2016).

Table 3: Shapiro Wilk test for normality

Parameter	*Shapiro Wilk test statistic (W)*	*Probability(p value)*
Plant height	0.9566	0.373
Number of leaves per plant	0.9250	0.075
Total biomass	0.9639	0.522
Grain yield	0.9539	0.328
Leaf area index (LAI)	0.9533	0.318
Crop water stress index (CWSI)	0.9268	0.083
NDVI	0.9838	0.954
WDRVI	0.9481	0.249
$CI_{red\text{-}edge}$	0.9544	0.336
CI_{green}	0.8937	0.016

Significant value ($p<0.05$) means the observation not normally distributed.

3.10 Assessment of the usefulness of coarse satellite images for monitoring maize crop condition and yields

Landsat 8 images were assessed for percentage cloud cover over time to identify likely effect of clouds on VIs derived from them. Image classification was performed by using Semi-Automatic Classification Plugin (SCP) available in QGIS. Congedo *et al.* (2013) and Congedo, (2013) describe SCP as easy plugin that allows for the collection of training areas through a region-growing algorithm (i.e. the selection of homogeneous pixels around a seed pixel of the image). The collected training areas have the advantage of being spectrally homogeneous, and therefore allow for a better definition of identified classes. Macro and micro "cloud" and "No cloud" classes were identified and maximum likelihood (ML) classification algorithm was used. ML is a supervised classification method based on Buyes theorem which makes use of a discriminant function to assign pixel to class with the highest likelihood (Ahmad and Quegan, 2012). The spectral signatures of training areas for "cloud" and "No cloud" were automatically calculated and displayed in the spectral signature and retrieved as percentage cloud cover in comma separated values (csv) format. Figure 9 depicts study area SUA experimental and Magadu farmers' fields over laid on 10 km by 10 km subset 11 bands satellite images displayed as Red-Green-Blue (RGB 123) band combination and their corresponding classification images represented in red (cloud) and yellow (no cloud) areas.

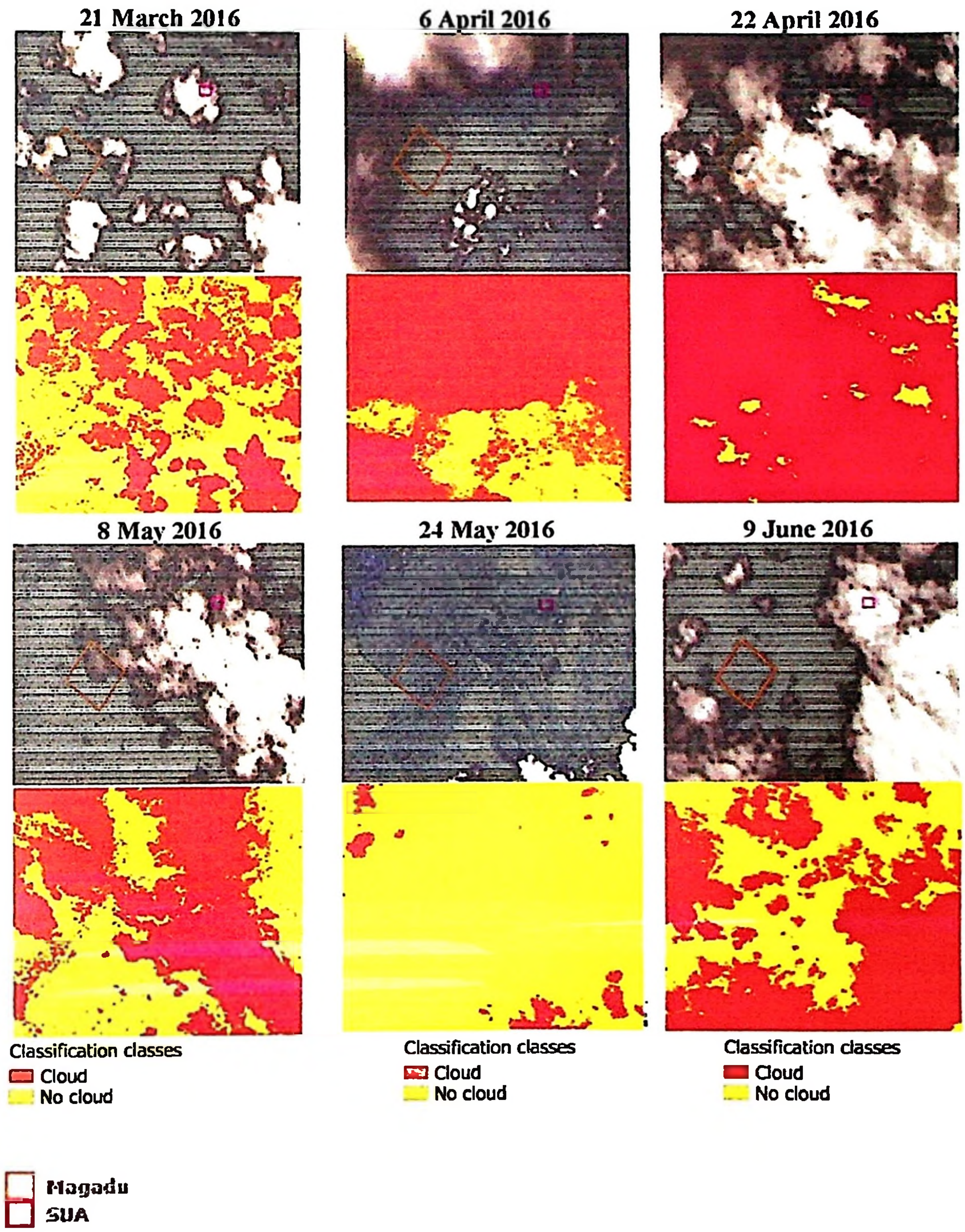

Figure 9: Raw and classified images using SCP and maximum likelihood supervised classification.

Paired sample t-test was carried out to investigate if the VIs derived from Landsat 8 were significantly different from those obtained from UAV imagery. Forty two pairs of VIs were formed based on date and day after sowing of which each pair constituted of NDVI, CI_{green}, and WDVI derived from Landsat 8 and UAV. Computed t-values were compared against the null hypothesis that the difference between Landsat 8 and UAV derived index is equal to zero.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Weather conditions and field operations

Figure 10 shows the distribution of the 10-day accumulated rainfall and evaporation, sowing date (A) and irrigation window (B). Sowing was done on 9 March 2016 (point A) after first rainfall obtained during dekad 1 of March. The evaporation was extremely higher (50 mm and 65 mm) than rainfall (5 mm and 50 mm) during March dekads 2 and 3 respectively, thus supplementary irrigation was carried out (irrigation window B) on 17/3, 18/3, 22/3, and 29/3/2016 to reduce moisture deficits to a crop. The month of April was the wettest period in the season where rainfall was above evaporation with the highest value of about 120 mm recorded during dekad 3 of the month. Rainfall during April was above 60 mm per dekad (Figure 10), which resulted into waterlogging impeding crop growth and promoting weed infestation.

The availability of nitrogen and other nutrients may be reduced by waterlogging, which slows the rate of leaf growth and accelerates leaf death (Edwards, 2009). Effective weed control period in maize has been reported during the first four to eight weeks after sowing because weeds compete vigorously with the crop for nutrient and water (WMO, 2011). Weed infestation was high as a result four weeding were done on 24/3, 9/4. 27/4 and 25/5/2016 to minimize the effect of weed on crop and acquired less weed contaminated remote sensed data. Weeds directly affect maize growth and development and under high weed infestation completion for soil water and nutrients results into reduced plant vigour and yield. Pigeonpea establishment was slowed down and some failed as it grows best in well – drained soils and does not survive waterlogged conditions (Sheahan, 2012), which can have negative implications on anticipated increase in crop cover.

Data on sunshine duration was missing from 11 May due to lack of sunshine cards. Figure 10 indicates that there was about 70 % of bright sunshine hour during dekad 1 and 2 of March which decreased to about 35% during dekad 1, 2, and 3 of April, thereafter increasing in May 2016. Fewer sunshine hours indicate more hours of cloudy conditions which have negative effects on availability and quality of remote sense images. This in turn poses challenges in mapping *Masika* (March-April-May) cropping season. To cope with cloudiness conditions, Eberhardt *et al.* (2016) recommends the use of higher repetition rates satellite system such as Santinel-2 for agricultural monitoring system based on Landsat-like imagery, while UAVs can be appropriate for local studies to argument the observing capabilities.

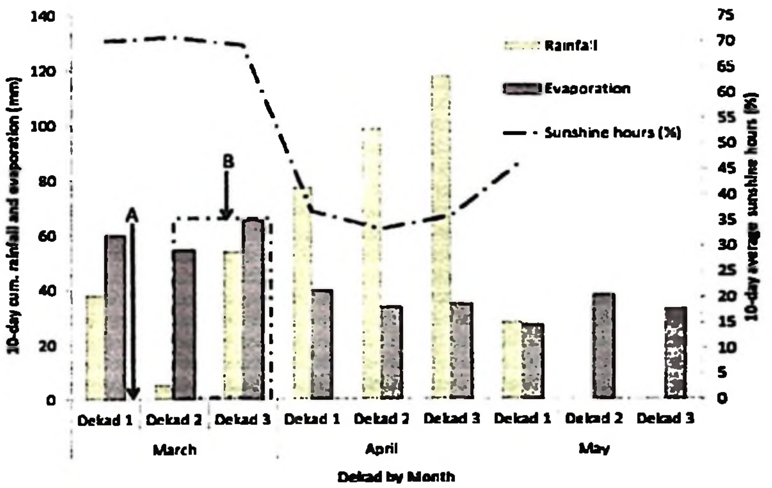

Figure 10: Seasonal distribution of; (a) rainfall, evaporation and duration of sunshine hours; the sowing date (A) and irrigation window (B).

4.2 Crop and remote sensed data exploration

Figure 11 and Figure 12 depict box plots for crop growth parameters and VIs respectively. For each plot the three horizontal lines of the boxes indicate the 75% percentile (up), median (solid line across boxes) and 25% percentile (bottom) for maize growth parameters

(Figure 11) and VIs (Figure 12). The upper and bottom bars outside the boxes show the maximum and minimum values respectively. Outliers are indicated by stars. Figure 11 shows that there was one outlier in CWSI. There were four outliers in CI_{green} and two outliers in LAI and WDRVI. There were no outliers in NDVI, plant height, number of leaves/plant, maize growth stage and $CI_{red\text{-}edge}$. These outliers were then removed from data before carrying out further analysis. Growth stage in Figure 11 indicates that there was fast growth for *Pannar* maize variety in treatments 2, 5, 7, and 8 where the maximum stage was about 80 days.

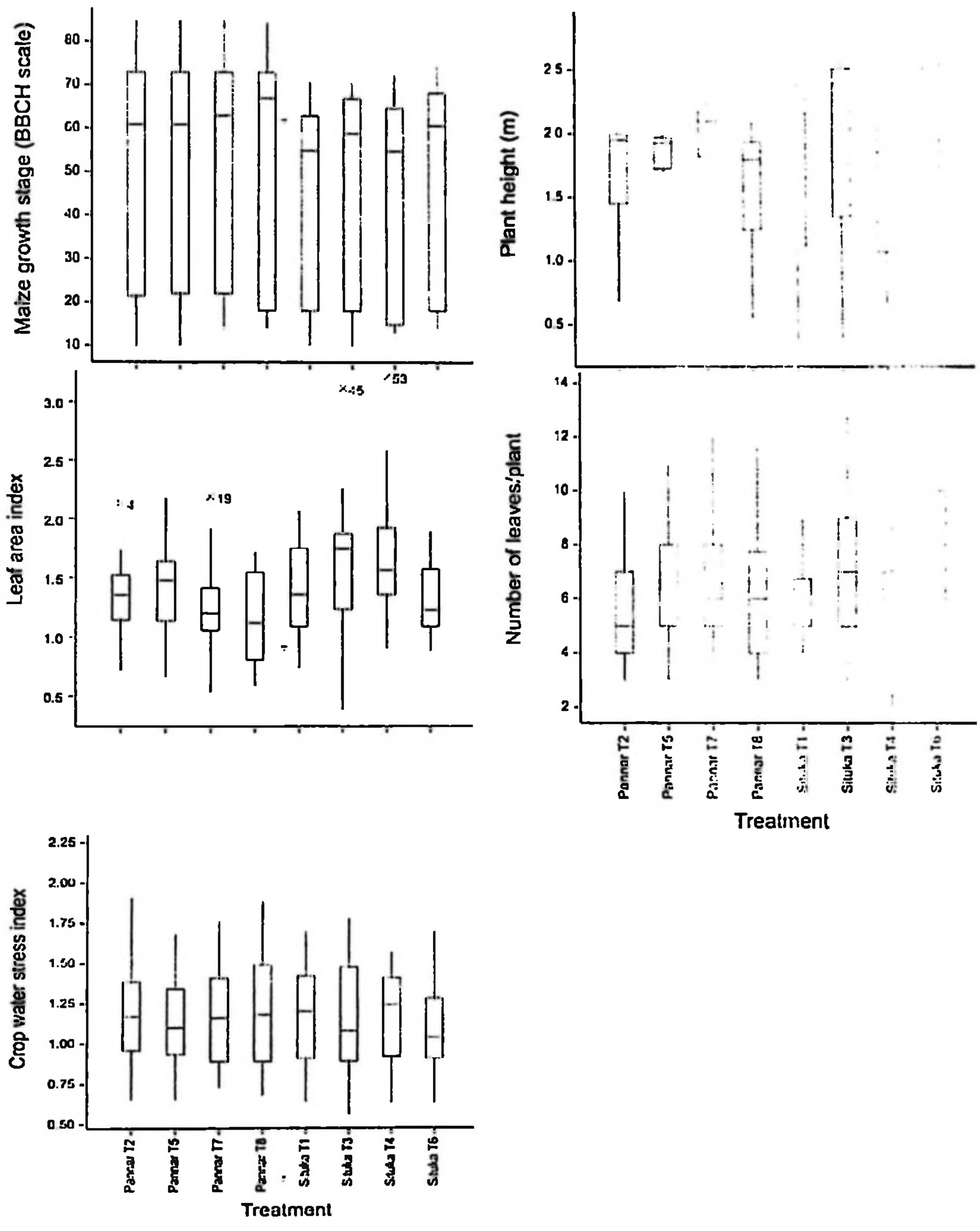

Figure 11: Box plots for maize condition parameters at different treatment combinations

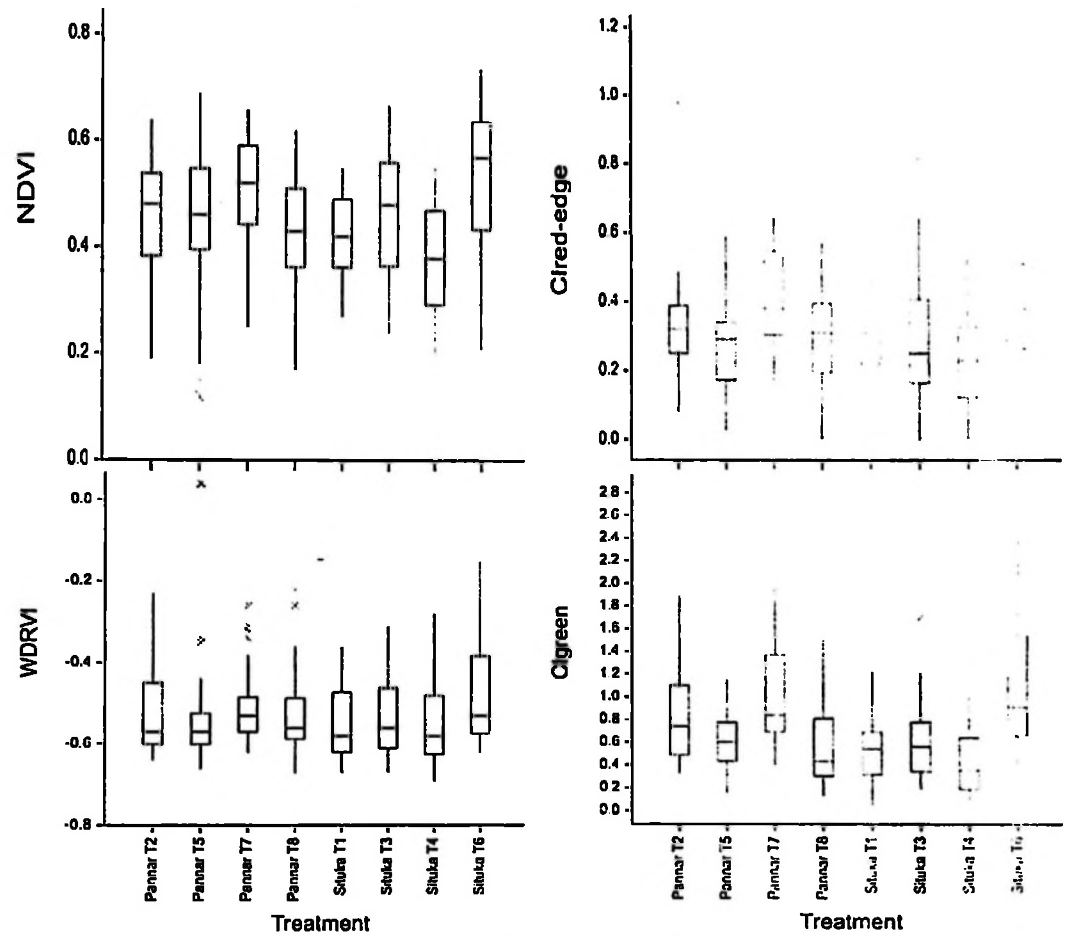

Figure 12: Boxplots for vegetation indices for maize varieties at different treatments where T1and T2= no pigeon pea intercropping, no fertilizer; T6 and T7 = no pigeon pea intercropping, fertilizer; T3 and T5= pigeon pea intercropping, fertilizer; T4 and T8 = pigeon pea intercropping, no fertilizer.

4.3 Plant parameters for evaluation of vegetation indices derived from fine and coarse remote sensing images

The section contains various results and discussion for the analysis performed on number of leaves per plant, plant height, LAI, CWSI, biomass and grain yield which later were used to evaluate the vegetation indices in sections 4.5 and 4.6.

4.3.1 Variations of plant parameters and their differentiation with days after sowing

Figure 13 (a-f) shows the variations of maize growth stage, height and number of leaves per plant after sowing for *Situka* and *Pannar* maize varieties grown with or without pigeon pea on fertilized and non-fertilized plots. Under fertilizer condition (Figure 13a) ***Pannar*** intercropped with pigeon pea depicted better growth (BBCH 60) from day 60 after sowing, while *Situka* intercropped with pigeon pea was the slowest for both fertilizer and non-fertilizer plots (Figure 13 a & b). Variation on growth stages indicates that *Pannar* had fast development compared to *Situka as* depicted mainly by non-fertilized plots. These results indicate that, pigeon pea intercropping and fertilizer application on maize could not influence variation in growth stages within the same variety. Thus, there was a clear crop stage differentiation between maize varieties from 60 to 92 DAS, the feature which was not observed within varieties. Early maturing maize varieties have been reported as ideal for intercropping by providing less competition for moisture, light, and nutrients than late maturing ones (Bello *et al.*, 2012).

Plant height was higher for *Situka* maize variety, with peak height attained at about 60 DAS for fertilizer plots (Figure 13c) and 68 DAS (Figure 13d) for non-fertilizer plots. Distribution of plant heights indicates that *Pannar* had shorter heights and reached peak height earlier (52 DAS) than *Situka* (60 DAS). Intercropping had negative effect on plant height for both maize varieties as indicated by shorter plant heights observed under pigeon pea intercropping. Intercropping increase space between primary crops leading to low crop density. Fertilizer application increased plant height to above 2.5 m for *Situka* as depicted by fertilizer plot and below 2.5 m for non-fertilizer plot.

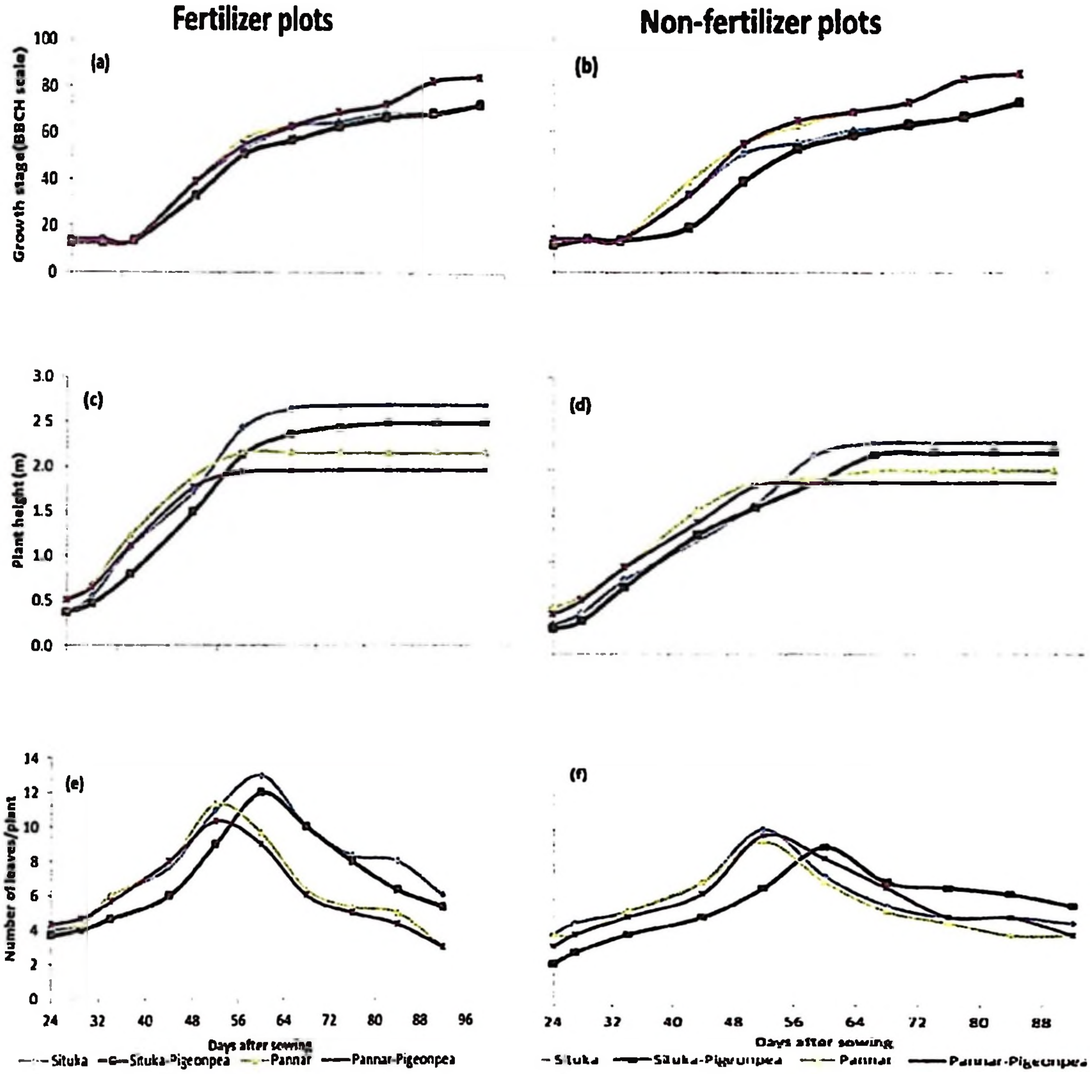

Figure 13: Variation of maize growth stages, plant height, and number of leaves per plant for *Situka* and *Pannar* maize varieties grown as sole crop and pigeon pea intercropped under fertilizer conditions (a), (c), and (e); and non- fertilizer condition (b), (d), and (f).

The results are consistent with Yin *et al.* (2011) who reported the existence of the significant positive response of plant height on N-fertilizer application during 10 and 12 maize leaf growth stages. Study by Karki *et al. (2015)* revealed higher plant heights were related with closely spaced than widely spaced maize, indicating that plant heightening was due to the effect of interplant competition for light, water, and nutrients.

Variations of number of leaves for the two varieties (Figure 13 e and f) indicates that under fertilized condition, *Situka* grown without intercropping had higher number of leaves (between 12 and 14 leaves/plant), while *Pannar* grown with pigeon pea had the lowest number of leaves per plant (less than 10 leaves). Similarly, the non-fertilizer plots depicted less number of leaves per plant, whereby *Pannar* without intercropping and *Situka* under intercropping depicted less number of leaves per plant; and the rate of decrease of green leaves (senescence) was higher for maize that was not intercropped with pigeon pea. *Pannar* has a lowest number of leaves, and its peak value was reached earlier than *Situka* indicating its early maturity (Figure 13). These results partly support Sangoi and Salvador (1997) and Bello *et al.* (2012) who found that the number of leaves per plant was only affected by cultivar, thus short season maize varieties were smaller and had the lowest number of leaves per plant. This was true under fertilizer condition (Figure 13e), but for non-fertilizer condition the difference between *Pannar* and *Situka* leaf number per plant was marginal. The number of leaves per plant for *Situka* further reduced under pigeon pea intercropping (Figure 13f), probably due to low nutrient competition ability of late maturing maize variety under pigeon pea intercropping. Two points were identified on Figure 13(e & f) as number of leaves per plant differentiation windows where the maximum number of leaves occurred for *Panna* (52 DAS) and *Situka* (60 DAS).

Figure 14 indicates the variation of CWSI and LAI with DAS. Variety differentiation with CWSI parameter occurred at 60 and 68 DAS for fertilizer and non-fertilizer conditions respectively (Figure 14a & b). *Situka* without intercropping depicted the lowest CWSI during parameter differentiation for both fertilizer and non-fertilizer plots. *Pannar* without pigeon pea intercropping experienced the highest CWSI at 60 DAS (fertilizer plots) and intercropped *Pannar* at 68 DAS (non-fertilizer plot).

Fertilized plots had higher LAI than non-fertilized plots for both maize varieties grown irrespective of the cropping pattern used (Figure 14c and d). *Pannar* grown without pigeon pea reported the highest LAI before 60 DAS, while *Situk*a grown under the same conditions remaining higher on fertilized plots after 60 DAS. These results are in support by Puntel (2012) who reported that low N supply lead to decrease in individual leaf area. Another study (Lukeba *et al.*, 2013) has reported that the differences observed in the maximum LAI, the growth rate and the rate of senescence in maize can be explained by varietal differences, field and/or environmental condition.

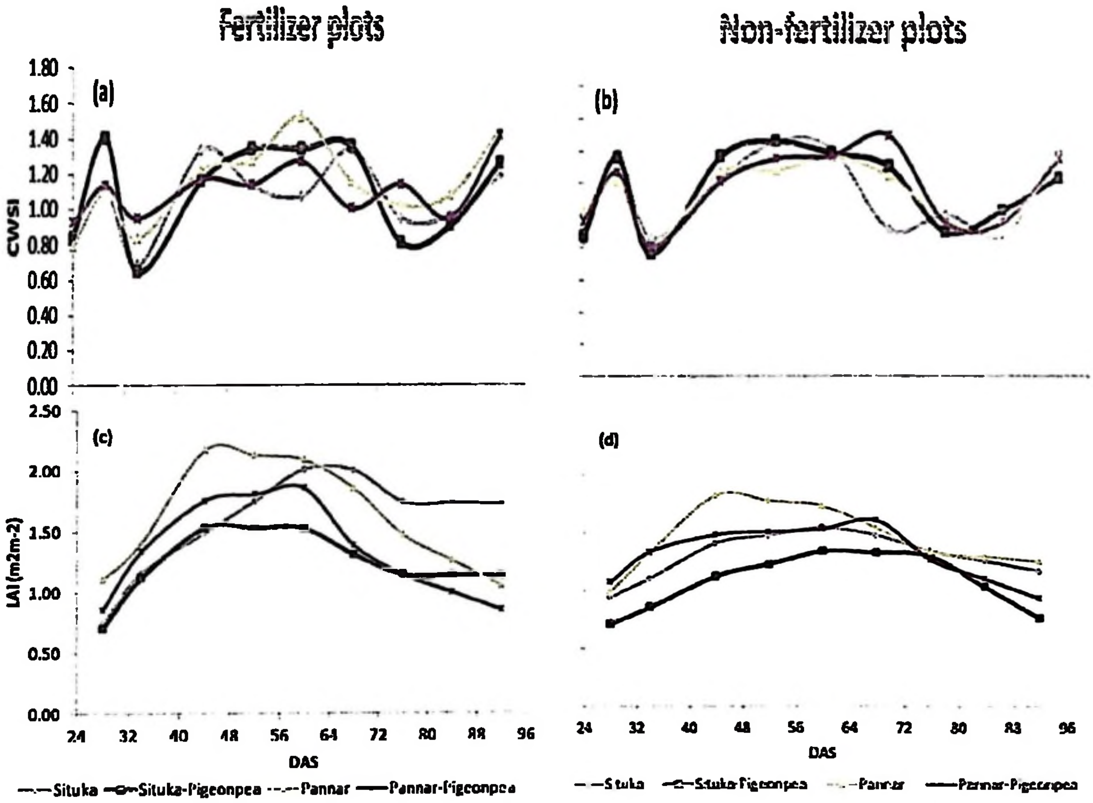

Figure 14: Variation of CWSI and LAI with DAS for *Situka* and *Pannar* maize varieties grown as sole crop and pigeon pea intercrop under fertilizer conditions (a) and (c); and non- fertilizer condition (b) and (d).

4.3.2 Biophysical parameter differentiation windows

Gradient analysis of maize biophysical parameters (number of leaves per plant, plant height, CWSI, and LAI) was used to identify period (s) when there was clear differentiation within the same variety or between different varieties. Table 4 shows the gradient analysis of number of leaves per plant, plant height, CWSI, and LAI computed for Panna and Situka maize varieties grown as sole crop or intercropped with pigeon pea on fertilized and non-fertilized plots. Parameter differentiation was either between different varieties, within same variety or at the peak. Differentiation between varieties was possible by using number of leaves per plant and plant height at DAS 52 (for fertilizer maize plots only), and LAI at DAS 44 on non-fertilizer plots. The CWSI could not differentiate between Pannar and Situka maize varieties for the period between 44 to 68 DAS. This was expected because the CWSI is an indicator of water stress status during the soil drying period, but that particular window reported sufficient rainfall in April. However, CWSI depicted differentiation within variety indicating that intercropping and fertilizer application had effect on variety response to water stress. Differentiation between sole and pigeon pea intercropped maize was possible for Situka at 44 DAS (fertilizer plots) and 68 DAS (non-fertilizer maize plots), and Pannar at 68 DAS (fertilizer plots) and 60 DAS (non-fertilizer maize plots).

For all identified within variety differentiation windows, the effect of water stress was decreasing on sole maize except for pigeon pea intercropped *Situka* that depicted decrease at 68 DAS under non-fertilizer conditions. There was differentiation between number of leaves per plant for sole and intercropped *Situka* only under non-fertilizer condition (52 DAS - not indicated in color). There was no differentiation within variety window detected on plant height. LAI shows differentiation between sole and pigeon pea intercropped *Pannar* under non-fertilizer condition at 60 DAS.

Table 4: Gradient analysis for crop biophysical parameters differentiation windows

(a) Number of leaves per plant								
	Fertilizer plot				Non-fertilizer plot			
Day after sowing (DAS)	44	52	60	68	44	52	60	68
Situka (Sole)	0.42	0.25	-0.38	-0.21	0.38	-0.33	-0.21	-0.08
Situka-Pigeon pea	0.38	0.38	-0.25	-0.25	0.21	0.29	-0.25	-0.04
Pannar (sole)	0.42	-0.21	-0.33	-0.21	0.29	-0.29	-0.21	-0.08
Pannar (pigeon pea)	0.28	-0.17	-0.38	-0.13	0.42	-0.17	-0.21	-0.21
(b) Plant height								
Situka (Sole)	0.09	0.03	0.00	0.00	0.05	0.07	0.02	0.00
Situka-Pigeon pea	0.08	0.03	0.00	0.00	0.04	0.03	0.04	0.00
Pannar (sole)	0.04	0.00	0.00	0.00	0.04	0.00	0.00	0.00
Pannar (pigeon pea)	0.02	0.00	0.00	0.00	0.05	0.00	0.00	0.00
(c) CWSI								
Situka (Sole)	-0.03	-0.01	0.03	-0.05	0.03	-0.01	-0.06	0.01
Situka-Pigeon pea	0.02	0.00	0.00	-0.07	0.01	-0.01	-0.01	-0.05
Pannar (sole)	0.01	0.03	-0.05	-0.02	0.00	0.01	-0.02	-0.03
Pannar (pigeon pea)	0.00	0.02	-0.03	0.02	0.02	0.00	0.02	-0.07
(d) LAI								
Situka (Sole)	0.06	0.01	0.00	-0.03	0.01	0.01	-0.01	-0.02
Situka-Pigeon pea	0.00	0.00	-0.03	-0.02	0.03	0.00	0.00	0.00
Pannar (sole)	-0.02	0.01	-0.03	-0.05	-0.03	0.02	-0.02	-0.03
Pannar (pigeon pea)	0.00	0.01	-0.06	-0.03	-0.02	0.02	0.01	-0.04

Key:

- Within variety differentiation window
- Between varieties differentiation window
- Peak biophysical parameters differentiation window

The peak number of leaves was attained earlier between 44 and 52 DAS for *Pannar* under fertilizer and non-fertilizer conditions. The period to peak number of leaves per plant for *Situka* was highly influenced by fertilizer application and intercropping. Under fertilizer conditions the peak number of leaves for sole and pigeon pea intercropped *Situka* maize variety was between 52 and 60 DAS. Under non-fertilizer conditions the peak number of leaves per plant was much earlier for sole maize (between 44 and 52 DAS) than intercropped *Situka* (between 52 and 60 DAS). Similarly, *Pannar* reached maximum plant height between 44 and 52 DAS for both fertilized and non-fertilized plots. However, there was a delayed peak plant height for *Situka* grown without fertilizer (between 60 and 68 DAS) compared to fertilized maize plots (between 52 and 60). These results indicate that there was early leaf senescence for *Pannar* than *Situka* maize varieties and the effect of fertilizer application and pigeon pea intercropping delayed period to maximum number of leaves per plant and plant height for non-fertilized *Situka* maize plots. Detecting early senescence in maize has been reported important because it can have a direct influence on yield (Kibet, 2016). Karki *et al.* (2015) described the effect of spacing in maize, highlighting that when plants are closely spaced, the increase shading effect of the bottom of the plants accelerates the plant growth. Sangoi and Salvador (1997) found from the experiment with maize genotypes that the height of the plant was significantly influenced by the plant density.

Table 4 also shows that the peak LAI was reached between 52 and 60 DAS for both maize varieties, except sole *Situka* under fertilizer condition that depicted delayed peak LAI, occurring between 60 and 68 DAS. In Table 4, the positives indicate increase and negative a decrease showing that the value obtained for a given biophysical parameter at day 8 after this date (DAS) was higher (increase) or lower (decrease) than the current values. Zero (0) indicates the peak or maximum point on curve. For each DAS: (1) the same sign within variety but different from another variety shows differentiation between varieties was possible using given biophysical parameter: (2) the same variety but different signs for (sole and pigeon pea intercropped maize) show differentiation within varieties was possible.

4.3.3 The effect of fertilizer, maize variety and intercropping on maize biophysical parameter differentiation

Fertilizer increased the number of leaves per plant, and the difference between fertilizer (11 leaves/plant) and non-fertilizer plots (8 leaves per plant) was highly significant ($p < 0.001$). The effect of maize variety and pigeon pea intercropping on number of leaves per plant was not significant (variety, $p = 0.547$; pigeon pea intercropping, $p = 0.383$) at 5% probability level. However, the number of leaves per plant for *Situka* was higher than *Pannar,* while intercropping pigeon pea with maize reduced the number of leaves for an average of one leaf per plant.

Table 5 further shows that the observed differences in plant heights was significantly induced by fertilizer application, variety type, and intercropping maize with pigeon pea. The maize heights (2.32 m) on fertilized plots was higher than the height (2.03 m) on non-fertilized maize plots, and the difference between the two was highly significant ($p < 0.001$). The difference between *Situka* (2.34 m) and *Pannar* (2.01 m) plant heights was highly significant ($p < 0.001$). The effect of pigeon pea intercrop on maize height. led to a significant difference between maize planted without pigeon pea intercropping (average height 2.3 m) and with pigeon pea (average height 2.1 m) at 5% probability level ($p < 0.020$). Intercropping and non-fertilizer conditions led to a significant decrease in plant heights. These results are different from Blaes *et al.* (2016) who found maize height was not responding strongly to fertilization. However, results of this study are consistent to Yin *et al.* (2011) and Puntel (2012) who reported on the positive response of plant height on fertilizer application. AlKhalifah (2013) noted that stem elongation response is activated at higher densities due to plant ability to distinguish neighboring plants by detecting a low red: far-red ratio leading to taller heights while, the shorter plants are due to more upright leaf angles and improved plant populations that permit more light penetration into the canopy resulting in an increased red: far-red ratio and delayed stem elongation.

Table 5: Significance test of the effect of fertilizer, maize variety, and pigeon pea intercropping on maize biophysical parameters differentiation

Variates: Crop biophysical parameters	Fertilizer			Maize variety			Pigeon pea intercropping		
	Yes	No	t-test (p)	Pannar	Situka	t-test (p)	Yes	No	t-test (p)
Leaves/plant	10.67	8.37	**<0.001**	9.33	9.71	0.547	9.25	9.79	0.383
Plant height (m)	2.32	2.03	**<0.001**	2.01	2.34	**<0.001**	2.08	2.28	**0.020**
LAI	1.53	1.33	**0.041**	1.48	1.37	0.296	1.27	1.58	**<0.001**
CWSI	1.22	1.24	0.865	1.23	1.23	1.000	1.29	1.17	0.387
Maize stage	70	68	0.681	74	64	**<0.001**	69	70	0.755
Biomass yield	6.44	4.45	**0.022**	6.02	4.87	0.207	4.16	6.73	**0.002**
Grain yield	2.43	1.58	0.057	2.62	1.40	**0.004**	1.45	2.56	**0.010**

Leaves/plant (n = 48, DAS =52, 60); Plant height (n = 48, DAS = 60, 68); LAI (n = 72, DAS = 44, 68, 92); CWSI (n = 24, DAS = 68); maize stage in BBCH scale (n = 48, DAS = 60, 92); and final biomass (n=24, DAS = 125) and grain yield (n = 24, DAS = 132). Bold values are p ≤ 0.05 resulted from two-sample t-test (one variate with group factor) and degrees of freedom (df) = n-2.

Table 5 indicated that there was a significant effect on maize LAI induced by fertilizer application and pigeon pea intercropping. The maize LAI of fertilized plots were higher than those obtained from non-fertilizer plots, and the difference between the two was significant ($p < 0.05$). There was a significant difference ($p < 0.001$) between LAI for maize planted without pigeon pea intercropping (1.58) against LAI (0.27) obtained from intercropped maize. Although *Pannar* recorded higher LAI than *Situka* but their difference was not statistically significant ($p = 0.296$) at 5% probability level.

Table 5 further shows that neither fertilizer nor maize-pigeon pea intercropping had significant effect on maize growth stage. Despite the insignificance effect of fertilizer application and pigeon pea intercropping, sowing without fertilizer and pigeon pea intercropping with maize delays crop maturity irrespective of the variety. There was a significant difference between *Pannar* and *Situka* growth stages ($p < 0.001$), with an average time lag of 10 days for *Situka* behind early maturing *Pannar*. These results indicate that maize growth stage is an attribute of variety rather than fertilizer and intercropping.

Biomass yield was higher under fertilizer (6.44 t/ha) against non-fertilizer conditions (4.45 t/ha), and the difference was significant ($p < 0.05$). The difference between sole maize biomass (6.73 t/ha) and pigeon pea intercropped maize (4.16 t/ha) was significant ($p = 0.01$). These results indicate that fertilizer application increased biomass while pigeon pea intercropped with maize reducing it (Table 5). This study could not establish any statistical evidence for the effect of variety on biomass yields between *Pannar* and *Situka* maize varieties, although *Pannar* produced higher *biomass* (6.02 t/ha) than *Situka* (4.87).

Yield response on fertilizer, maize variety, and pigeon pea intercropping indicates that the effect of fertilizer on maize grain yields was not significant, while different varieties and pigeon pea intercropping with maize resulted into a significant variation in grain yield. *Pannar* produced high grain yield (2.62 t/ha) against *Situka* (1.4 t/ha), and the difference of 1.22 t/ha was significant ($p < 0.01$).

There was no significant effect on CWSI induced by fertilizer application, maize variety, or pigeon pea intercropping. This probably was due to the soil moisture experienced during the growing season (April 2016 was a month with high amount of rainfall and minimal evaporation in the study area) as reported in section 4.1.

These results reveal that fertilizer application had positive significant implication on number of leaves per plant ($p < 0.001$), maize height ($p < 0.001$), LAI ($p < 0.05$), and biomass yield ($p < 0.05$). The effect of variety type was significant on plant height ($p < 0.001$), maize growth stage ($p < 0.001$), and grain yield ($p < 0.01$), while pigeon pea intercropped with maize significantly reduced plant height ($p < 0.05$), LAI ($p < 0.001$), biomass ($p < 0.01$), and grain yields ($p = 0.01$). The results are consistent with previous findings (Kimaro *et al.*, 2009) where intercropping with pigeon pea enhanced maize yield over sole maize only when fertilized, thus reflecting probable nutrient competition. It was emphasized that maize has faster root development and a higher rate of above ground biomass which strongly competes for nutrient in the surface soil with pigeon pea, thus Amare *et al.* (2012) indicated a delayed sowing of pigeon pea two to three weeks after maize sowing date may reduce competition.

4.3.4 Relationship between (biomass and grain) yields and other maize biophysical parameters

Biomass and grain yields were correlated with number of leaves per plant, plant height, LAI, CWSI, and crop growth stage (Table 6). The data was based on field observation averaged for each treatment combination during the period of parameter differentiation. The results indicate that, there was a significant positive correlation between mean number of leaves per plant and biomass at 52 DAS ($r = 0.72$, $p < 0.001$), and grain yield ($r = 0.74$, $p < 0.001$). There was no significant correlation between number of leaves per plant and biomass and grain yield at 60 DAS. There was positive relationship between number of leaves per plant and CWSI, and grain yield though the correlations were not statistically significant ($p > 0.05$). Plant height indicated positive significant correlation with LAI ($r = 0.57$, $p < 0.01$), biomass ($r = 0.63$, $p < 0.001$), grain yield ($r = 0.42$, $p < 0.05$). Although the correlation between plant height and grain yield shows a significant positive relationship but low correlation and precision ($p < 0.05$), may limit the conclusion that taller maize have higher yields than shorter ones.

There was a significant positive correlation between LAI and biomass ($r = 0.57$, $p < 0.01$), and grain yield (DAS 52; $r = 0.72$, $p < 0.001$), indicating that high LAI can be related with total biomass and final yield. Green LAI profiles during reproductive stages can be used to detect variability in maize grain yield (Guindin-Garcia, 2010).

Table 6: Correlation matrix for crop biophysical parameters based on identified parameter differentiation windows

Crop biophysical parameter	Differentiation window (DAS)	Biomass	Grain yield
Number of Leaves/plant	52	0.72***	0.74***
	60	0.24ns	0.07ns
Plant height	60	0.58**	0.35ns
	68	0.32 ns	0.04ns
LAI	44	0.53**	0.62**
	68	0.57**	0.59**
	92	0.55*	0.30ns
CWSI	68	-0.10ns	-0.08ns
Maize stage (BBCH scale)	60	0.45*	0.54**
	92	0.33ns	0.62**

*Values followed by *, **, and *** represent probability (p) ≤ 0.05, 0.01, and 0.001 respectively. ns = not significant. Correlations were tested against zero (r≠0)*

4.4 Variation of vegetation indices for different farming practices and fertilizer application

4.4.1 Variation of VIs signatures of maize with day after sowing

The variations of NDVI (a, b) and $CI_{red\text{-}edge}$ (c, d), and CI_{green} (e, f), and WDRVI (g, h) signatures with number of days after sowing (DAS) for *Situka* and *Pannar* maize varieties grown as sole crop and pigeon pea intercropping under fertilized and non-fertilized soil conditions is presented in Figure 15 and Figure 16 respectively. Figure 15 shows that the peak NDVI was early for *Pannar* (DAS 44) and occurred later for *Situka* (DAS 52) on both (a) fertilizer and (b) non-fertilizer plots. This indicated their differences in maturing period. The NDVI values at the peak were higher for *Situka* under fertilizer condition, while depicting opposite scenario on a non-fertilizer plots. The observed NDVI variations Figure 15 (a, b) indicates higher response of *Situka* on fertilizer application than *Pannar*. Planting maize on non-fertilizer plots decreased NDVI values, but larger negative effect was observed on *Situka* than P*annar (*Figure 15b*)*. The effect of pigeon pea intercropped with maize on NDVI was only discernable within maize varieties till 68 DAS where NDVI of the same maize variety was low irrespective of fertilizer application. Two points (52 and 60 DAS) indicated large separation and were selected as index differentiation windows.

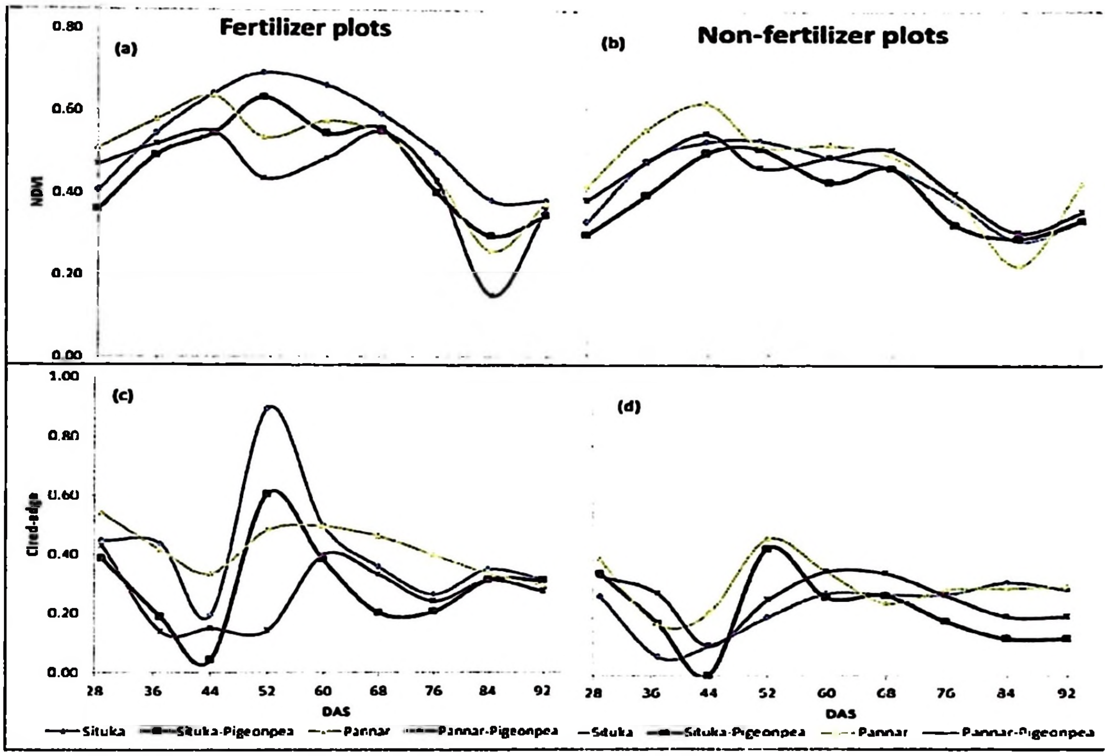

Figure 15: Variation of NDVI (a, b) and $CI_{red\text{-}edge}$ (c, d) with days after sowing (DAS) for *Situka* and *Pannar* maize varieties grown as sole crop and pigeon pea intercropping under fertilized and non-fertilized field plots.

Figure 15c and d indicate that $CI_{red\text{-}edge}$ was decreasing during early crop stages reaching a minimum at 44 DAS on both fertilizer and no-fertilizer maize plots. There was clear differentiation between varieties due to difference in maximum $CI_{red\text{-}edge}$ values and DAS at the peak for maize grown on fertilized plots. $CI_{red\text{-}edge}$ peak values occurred at 52 DAS (*Situka*) and 60 DAS (*Pannar*), with sole *Situka* reporting the highest $CI_{red\text{-}edge}$ (9.5), followed by pigeon pea intercropped *Situka* (6.2), sole *Pannar* (0.5) and the lowest was pigeon pea intercropped *Pannar* (0.4). Contradicting results to fertilized plots was observed under non-fertilizer plots, where sole *Pannar* had the highest $CI_{red\text{-}edge}$ and earlier peak (52 DAS) while the sole *Situka* depicted the lowest values and delayed peak (60

DAS). Figure 16(a, b) indicates that there was increase in CI_{green} reaching peak values at 52 DAS for sole and intercropped *Situka* and sole *Pannar* under fertilizer conditions. Two peak CI_{green} maxima were observed for *Pannar* intercropped with pigeon pea at 60 and 76 DAS under fertilizer application. These results are similar to Kibet (2016) who found the optimal period for predicting maize yield using multi-temporal VI data to be at fruit development stage of maize growth which occurred between 60 and 75 DAS. Under non-fertilizer conditions, the peak maximum CI_{green} was at 52 DAS for *Situka* (intercropped) and *Pannar* (sole) and delayed peak at 68 DAS for *Situka* (sole) and *Pannar* (intercropped). There was a clear differentiation within varieties at the peak maximum CI_{green}, the feature which was not depicted within same variety. Figure 16 (c, d) shows that early WDRVI differentiation between *Pannar* and *Situka* maize varieties was at 52 DAS with the index peak maximum occurring at 76 DAS for fertilized crop. The WDRVI at 52 DAS was higher for *Situka* than sole *Pannar* while sole maize recording higher values than intercropped maize of same variety.

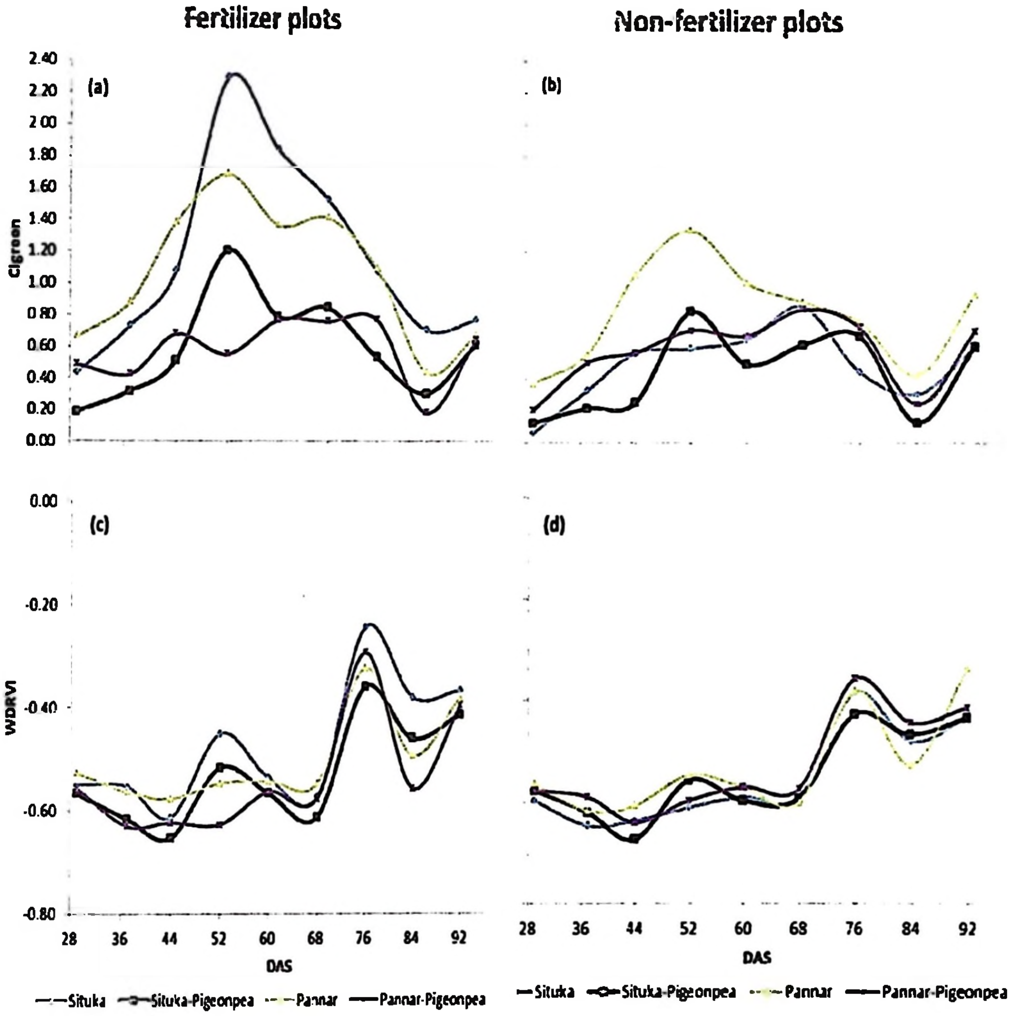

Figure 16: Variation of CI_{green} (a, b) and WDRVI (c, d) with DAS for *Situka* and *Pannar* maize varieties grown as sole crop and pigeon pea intercropping under fertilized and non-fertilized field plots.

The NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI depicted high values for both maize varieties grown without pigeon pea in fertilized plots. For non-fertilized plots, *Pannar* indicated better performance by registering higher VIs values than *Situka* for both sole and pigeon pea intercropped plots. There was poor performance for *Situka* intercropped with pigeon pea in spite of fertilizer application, indicating varietal differences for overcoming the effect of nutrient competition revealed by pigeon pea on maize (Kimaro *et al.*, 2009; Amare *et al.*, 2012). The higher and lower VIs values depicted under fertilized and non-fertilized maize plots respectively may be related to differences in leaf Nitrogen (not in the scope of this study). Reporting on the effect of fertilizer on spectral values Mondal *et al.* (2011) cited Serrano *et al.* (2000) noted that the leaves with higher nitrogen content have stronger spectral reflectance in NIR wave bands (higher VIs) and leaves with nitrogen stress, resulting in lower chlorophyll content, reflect more in red spectral region (lower VI). Figure 15 and 16 indicates that there was no temporal agreement on trends and peaks amongst VIs tested, with exception of WDRVI observed maximum peak values during fruit development (BBCH 73) at 76 DAS the rest VIs depicted the peak maximum values at 52 DAS when the crop was at inflorescence emergence, heading stage (BBCH 53-55). Dissimilarities in VIs seasonal trends are due to the unique combination of wavebands of each VIs that have been related to a specific canopy parameter.

4.4.2 Treatment effect detection by vegetation indices at crop biophysical parameter differentiation windows

The observed vegetation indices were evaluated for their ability to detect if the effect of maize variety, pigeon pea intercrop, and fertilizer application treatment factors attributed to the differences identified on *Pannar* and *Situka* maize varieties by crop biophysical parameter at parameter differentiation windows. Table 7 shows the evaluation for effect of fertilizer, maize variety, and pigeon pea intercropping on maize as detected at specific biophysical parameter differentiation windows (44, 52, 60, and 68 DAS).

Table7: Effect of fertilizer, maize variety, and pigeon pea intercropping on maize as detected by vegetation indices for specific parameter differentiation window

Window(DAS)	*Vegetation index*	*Factors*								
		Fertilizer			Maize variety			Pigeonpea intercropping		
		Yes	No	t-test (p)	*Pannar*	*Situka*	t-test (p)	Yes	No	t-test (p)
44	NDVI	0.59	0.54	**0.026**	0.59	0.55	0.163	0.53	0.60	**0.002**
	$CI_{red\text{-}edge}$	0.18	0.11	0.099	0.20	0.09	**0.007**	0.07	0.21	**<0.001**
	CI_{green}	0.91	0.62	0.058	0.93	0.60	**0.041**	0.51	1.02	**<0.001**
	WDRVI	-0.62	-0.64	0.074	-0.61	-0.64	**0.007**	-0.65	-0.61	**<0.001**
52	NDVI	0.57	0.50	**0.048**	0.48	0.59	**0.004**	0.51	0.57	0.131
	$CI_{red\text{-}edge}$	0.53	0.35	0.223	0.34	0.54	0.199	0.36	0.51	0.326
	CI_{green}	1.43	0.87	0.067	1.07	1.23	0.614	0.83	1.48	**0.031**
	WDRVI	-0.53	-0.58	0.234	-0.58	-0.53	0.199	-0.57	-0.52	0.318
60	NDVI	0.57	0.48	**0.007**	0.51	0.53	0.703	0.48	0.56	**0.036**
	$CI_{red\text{-}edge}$	0.44	0.32	**0.004**	0.41	0.36	0.334	0.35	0.41	0.220
	CI_{green}	1.19	0.71	**0.026**	0.96	0.95	0.959	0.68	1.22	**0.014**
	WDRVI	-0.55	-0.58	**0.005**	-0.56	-0.57	0.336	-0.57	-0.56	0.204
68	NDVI	0.56	0.47	**0.006**	0.52	0.52	0.903	0.52	0.52	0.903
	$CI_{red\text{-}edge}$	0.34	0.29	0.265	0.35	0.28	0.088	0.29	0.34	0.265
	CI_{green}	1.14	0.81	**0.032**	0.98	0.96	0.935	0.77	1.17	**0.007**
	WDRVI	-0.58	-0.59	0.275	-0.57	-0.59	0.079	-0.59	-0.58	0.275

Bold values are $p < 0.05$ resulted from two-sample t-test (one variate with group factor) and number of observations n = 24; degrees of freedom (df) = n-2.

To find out if the width of the window was significant ($p < 0.05$), two closest parameter differentiation windows were averaged together to form a new and wide window (Table 8). Since the interval between two windows was 8 days, combining two windows widened the window from 8 to 16 days.

Results show that at early crop stages (44 DAS) the effect of fertilizer was detected only by NDVI, and there was a significant difference ($p < 0.05$) between fertilized and non-fertilized plots NDVI. There was significant difference between *Pannar* and *Situka* maize varieties identified by $CI_{red\text{-}edge}$ ($p < 0.01$), CI_{green} ($p < 0.05$), and WDRVI ($p < 0.01$). The effect of pigeon pea intercropping on maize at 44 DAS was depicted by all VIs tested, indicating that VIs values observed from sole maize were significantly higher than pigeon intercropped maize (NDVI, $p < 0.01$; $CI_{red\text{-}edge}$, CI_{green}, and WDRVI, $p < 0.001$). The differences detected by VIs for effect of fertilizer application, maize variety, and pigeon pea intercrop was reduced at 52 DAS except NDVI which observed a significant ($p < 0.01$) difference between *Situka (NDVI = 0.59)* and *Pannar (NDVI = 0.48)*. Other observed significant differences were for NDVI on fertilizer and non-fertilizer plots and CI_{green} for sole maize and intercropped maize ($p < 0.05$). Similarly, VIs depicted at 60 DAS were higher on fertilizer than non-fertilizer plots, where significant differences were for NDVI ($p < 0.01$), $CI_{red\text{-}edge}$ ($p < 0.01$), and CI_{green} ($p < 0.05$).

The effect of intercropping was detected by NDVI and CI_{green}, where these indices were higher for sole than intercropped maize, and the differences were significant ($p < 0.05$). The effect of fertilizer was again detected at 68 DAS by NDVI ($p < 0.01$) and CI_{green} ($p < 0.05$), and on intercropping, CI_{green} ($p < 0.01$).

Table 8: Effect of fertilizer, maize variety, and pigeon pea intercropping on maize as detected by vegetation indices averaged for two consecutive parameter differentiation windows

Window (DAS)	*Vegetation index*	Factors								
		Fertilizer			Maize variety			Pigeonpea intercropping		
		Yes	No	t-test (p)	*Pannar*	*Situka*	t-test (p)	Yes	No	t-test (p)
44	NDVI	0.58	0.52	**0.004**	0.53	0.57	0.132	0.52	0.58	**0.004**
&	$CI_{red\text{-}edge}$	0.36	0.23	0.144	0.27	0.31	0.657	0.22	0.36	0.102
52	CI_{green}	1.17	0.74	**0.015**	1.00	0.92	0.655	0.67	1.25	**<0.001**
	WDRVI	-0.58	-0.61	-0.127	-0.59	-0.59	0.757	-0.61	-0.57	0.077
52	NDVI	0.57	0.49	**<0.001**	0.50	0.56	**0.023**	0.50	0.56	**0.010**
&	$CI_{red\text{-}edge}$	0.49	0.33	**0.046**	0.37	0.45	0.339	0.36	0.46	0.187
60	CI_{green}	1.31	0.79	**0.005**	1.02	1.09	0.701	0.75	1.35	**0.001**
	WDRVI	-0.54	-0.58	**0.049**	-0.57	-0.55	0.344	-0.57	-0.55	0.174
60	NDVI	0.56	0.47	**<0.001**	0.52	0.52	0.839	0.50	0.54	0.105
&	$CI_{red\text{-}edge}$	0.39	0.31	**0.007**	0.38	0.32	0.070	0.32	0.38	0.105
68	CI_{green}	1.16	0.76	**0.002**	0.97	0.95	0.927	0.73	1.20	**<0.001**
	WDRVI	-0.56	-0.58	**0.009**	-0.57	-0.58	0.063	-0.58	-0.57	0.102

Bold values are $p < 0.05$ resulted from two-sample t-test (one variate with group factor) and number of observations n = 24; degrees of freedom (df) = n-2.

Of the four indices tested the effect of fertilizer was significantly reported by NDVI (44, 52, 60, and 68 DAS), $CI_{red\text{-}edge}$ (60 DAS), CI_{green} (60 and 68 DAS), and none for WDRVI. The effect of variety was significantly observed at 52 DAS by NDVI; and 44 DAS by $CI_{red\text{-}edge}$, CI_{green}, and WDRVI. The effect of pigeon pea intercropping was efficiently detected by all indices at 44 DAS. While NDVI was better in detecting the effect of fertilizer over the four windows studied in Table 7, the CI_{green} was capable to detect the negative effect induced by pigeon pea intercropping on maize across the windows.

Applying wide windows (44&52, 52&60, and 60&68 DAS) in Table 8, factor effect detection with NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI improved for fertilizer application and diminished for variety. However, the significant effect of pigeon pea intercropping on maize that was detected by $CI_{red\text{-}edge}$ and WDRVI at 44 DAS diminished at widened window (44&52 DAS). CI_{green} significance test levels remain high or improved on detection of the effect of pigeon pea intercropping on maize as depicted across the windows.

4.5 Relationship between crop parameters and vegetation indices derived from fine resolution UAV data

4.5.1 Relationship between mean seasonal VIs and crop growth parameters

Table 9 shows correlations between crop growth paramcters and vegetation indices from leaf development to fruit development phase without considering individual phenological phases. There was significant positive correlations between NDVI and number of leaves per plant ($r = 0.74$, $p < 0.001$); plant height ($r = 0.77$, $p < 0.001$), total biomass yield ($r = 0.75$, $p < 0.001$); grain yield ($r = 0.68$, $p < 0.001$); and LAI ($r = 0.59$, $p < 0.01$). The correlation coefficient between NDVI and number of leaves per plant (0.74), plant height (0.77), total biomass (0.75) and grain yield (0.68) indicate large ($p < 0.001$) and moderate ($p < 0.01$) relationship for LAI (0.59). This indicates that NDVI increases with increasing number of leaves, plant height, biomass and LAI which translates to increase in maize grain yield. Correlation coefficient between NDVI and CWSI was ($r = - 0.04$, $p > 0.05$) was not significant; however the negative relationship indicates that NDVI decreases with increasing water stress in maize. There were significant correlations between WDRVI and number of leaves per plant ($r = 0.67$, $p < 0.001$); plant height ($r = 0.64$, $p < 0.001$), total biomass yield ($r = 0.53$, $p < 0.01$); grain yield ($r = 0.53$, $p < 0.01$); and LAI ($r = 0.50$, $p < 0.05$). The correlation coefficient between WDRVI and number of leaves per plant (0.67), plant height (0.64), indicate strong relationship ($p < 0.001$),) while total biomass (0.53) and grain yield (0.53) depict moderate relationship ($p < 0.01$) and weak relationship for LAI (0.50).

Table 9: Correlation between mean seasonal VIs and crop biophysical parameters

Vegetation indices and crop parameters	Crop parameters					
	Number of leaves/plant	Plant height	LAI	CWSI	Biomass	Grain yield
NDVI	0.74***	0.77***	0.59**	-0.04ns	0.75***	0.68***
WDRVI	0.67***	0.64***	0.50*	-0.05ns	0.53**	0.53**
CI_{green}	0.56**	0.54**	0.76***	.01ns	.85***	0.83***
$CI_{red\text{-}edge}$	0.54**	0.57**	0.65***	0.09ns	0.61**	0.66***

Values followed by *, **, and *** are significant at 0.05, 0.01, and 0.001 probability level respectively. Probabilities are based on two sided t-test.

There was a significant positive correlation between CI_{green} and number of leaves per plant ($r = 0.56, p = 0.001$); plant height ($r = 0.54, p < 0.01$); LAI ($r = 0.76, p < 0.001$); biomass ($r = 0.85, p < 0.001$); and grain yield ($r = 0.83, p < 0.001$). Correlation between number of leaves per plant and CI_{green} were moderate ($p < 0.01$), and large ($p < 0.001$) with LAI, biomass, and grain yield indicating increase in CI_{green} is associated with increase of these parameters. CWSI did not depict any significant association with CI_{green}, although positive relationship existed. There were significant positive correlations between $CI_{red\text{-}edge}$ and number of leaves per plant ($r = 0.54, p < 0.01$); plant height ($r = 0.57, p < 0.01$); LAI ($r = 0.65, p < 0.001$); biomass ($r = 0.61, p < 0.01$); and grain yield ($r = 0.66, p < 0.001$). The strength of correlation coefficients between $CI_{red\text{-}edge}$ and LAI, and grain yield was large ($p < 0.001$) indicating that higher $CI_{red\text{-}edge}$ was associated with higher LAI and grain yield in maize. The observed low correlations and insignificant values for CWSI (Table 9) could be attributed to rainfall, thus CWSI became unsuitable for monitoring seasonal crop under conditions of high rainfall as it was observed during the cropping season in April 2016.

4.5.2 Relationship between VIs and crop growth parameters based on parameter differentiation windows

Results from correlation analysis (Table 10) indicate that there was a significant positive correlation between NDVI and number of leaves per plant (DAS 60, $r = 0.64, p < 0.001$); plant height (DAS 60, $r = 0.76, p < 0.001$); and LAI (DAS 44, $r = 0.57, p < 0.01$). There was no significant correlation detected (at $p < 0.05$) between NDVI and number of leaves per plant (52 DAS); and plant height, LAI, CWSI (68 DAS); and between NDVI and maize stage (60 DAS). There was positive significant correlation between $CI_{red\text{-}edge}$ and plant height (DAS 60, $r = 0.48$, $p<0.05$); LAI (DAS 44, $r = 0.70$, $p < 0.001$; DAS 68, $r = 0.58$, $p < 0.01$). Correlation coefficients observed between $CI_{red\text{-}edge}$ and number of leaves per plant (52 and 60 DAS); and plant height (68 DAS), CWSI (68 DAS); and between $CI_{red\text{-}edge}$ and maize stage (60 DAS) were not statistically significant at 5% probability level. There was positive significant correlation between CI_{green} and number of leaves per plant (DAS 52, $r = 0.42, p < 0.05$; DAS 60, $r = 0.55, p < 0.01$); plant height (DAS 60, $r = 0.68, p < 0.001$); and LAI (DAS 44, $r = 0.72, p < 0.001$; DAS 68, $r = 0.75, p < 0.001$). The correlations coefficients between CI_{green} and CWSI, and CIgreen and maize stage were not significant ($p > 0.05$) for selected windows. The WDRVI showed positive significant correlations with number of leaves per plant (DAS 60, $r = 0.42, p < 0.05$), plant height (DAS 60, $r = 0.49$, $p < 0.05$), and LAI (DAS 44, $r = 0.74, p < 0.001$; DAS 68, $r = 0.53, p < 0.01$). Similarly, relationship between WDRVI and CWSI and maize stage were not significant ($p > 0.05$). The observed positive correlations for 44, 52, 60, and 68 DAS windows imply the relationship that as the number of leaves per plant, plant height, and LAI increase, the NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI also increase.

Table 10: Correlation matrix between VIs and crop biophysical parameters based on identified maize biophysical parameter differentiation windows

Biophysical parameter	Differentiation window (DAS)	Vegetation indices			
		NDVI	$CI_{red\text{-}edge}$	CI_{green}	WDRVI
Number of Leaves/plant	52	0.22ns	0.21ns	0.42*	0.22ns
	60	0.64***	0.38ns	0.55**	0.42*
Plant height	60	0.76***	0.48*	0.68***	0.49*
	68	0.27ns	-0.04ns	0.33ns	-0.06ns
LAI	44	0.57**	0.70***	0.72***	0.74***
	68	0.23ns	0.54**	0.75***	0.53**
CWSI	68	0.10ns	0.01ns	-0.01ns	-0.03ns
Maize stage	60	0.35ns	0.24ns	0.35ns	0.27ns

Values followed by ns = not significant; those with *, **, and *** are significantly different from zero at 0.05, 0.01, and 0.001 probability level respectively following two sided t-test.

Relationship between VIs and LAI around flowering has been reported very useful for remote-sensing applications, especially when canopy cover was little related to the LAI during this phase (Liebisch *et al.*, 2015). CWSI has shown better performance when a crop was exposed to water stress (Bijanzadeh and Emam, 2012), becoming important in irrigation scheduling and early detection of plant stress induced by water stress more rapidly in dry land areas (WMO, 2011). Crop biophysical parameters are the attributes of biomass and grain yields. Relationship between VIs and biomass and grain yield is shown in Table 11.

Table 11: Correlation matrix between VIs and maize final biomass and grain yields for selected windows

Yields	Differentiation Window (DAS)	Vegetation indices			
		NDVI	$CI_{red\text{-}edge}$	CI_{green}	WDRVI
Biomass	44	0.89***	0.78***	0.85***	0.75***
	60	0.71***	0.70***	0.76***	0.70***
	68	0.47*	0.35ns	0.67***	0.33ns
Grain yield	44	0.86***	0.85***	0.89***	0.81***
	60	0.62**	0.72***	0.72***	0.71***
	68	0.43*	0.52**	0.60**	0.51**

Values followed by *, **, and *** represent probability (p) $\leq$ 0.05, 0.01, and 0.001 respectively. ns = not significant. Correlations were tested against zero ($r \neq 0$)

Biomass and grain yields depicted positive and statistically significant ($p < 0.05$) correlations with VIs for 44, 60, and 68 DAS except for DAS 68 that reported low and insignificant $CI_{red\text{-}edge}$ and WDRVI with biomass. The correlation coefficients were higher ($r \geq 0.75$) at 44 DAS decreasing with increasing DAS (between 44, 60, and 68) for both biomass and grain yields. These results are consistent with Wang *et al.* (2016) study that found the average VIs in the pre-maturity stage and for the whole growing season were statistically predictors of final yield. However, WMO (2011) noted that correlations at early crop development stage may not reflect final yield due to the reliability of imagery for use in yield estimation that decreases as the time before harvest increases because there are more opportunities for factors such as stress to influence yield. Hatfield and Prueger (2010) cautioned that when using these VIs care needs to be taken to ensure that the information being generated from the VI is appropriate for the specific part of the growing season. The results therefore indicate that 60 DAS was the optimum period for significant relationship between biomass, grain yield and VIs, thus required further investigation.

4.5.3 Evaluation of vegetation indices for the detection of the effect of fertilizer application and pigeon pea intercropping on maize biophysical parameters

4.5.3.1 Vegetation indices for detecting the effect of fertilizer on number of leaves per plant

Simple linear regressions between number of leaves per plant and VIs are shown in Figure 17(A-D). The CI_{green} ($R^2 = 0.54$) and NDVI ($R^2 = 0.64$) were the best indices for ***Pannar***, similarly $CI_{red\text{-}edge}$ ($R^2 = 0.61$) and WDRVI ($R^2 = 0.66$) for ***Situka*** maize variety under similar conditions. These results indicate that the effect of variety differences was more pronounced than fertilizer application where *Pannar* CI_{green} and NDVI had similar response as it was for ***Situka*** $CI_{red\text{-}edge}$ and WDRVI, probably due to inherent variety differences in canopy cover as depicted by number of leaves per plant, low for ***Pannar*** and high for *Situka*.

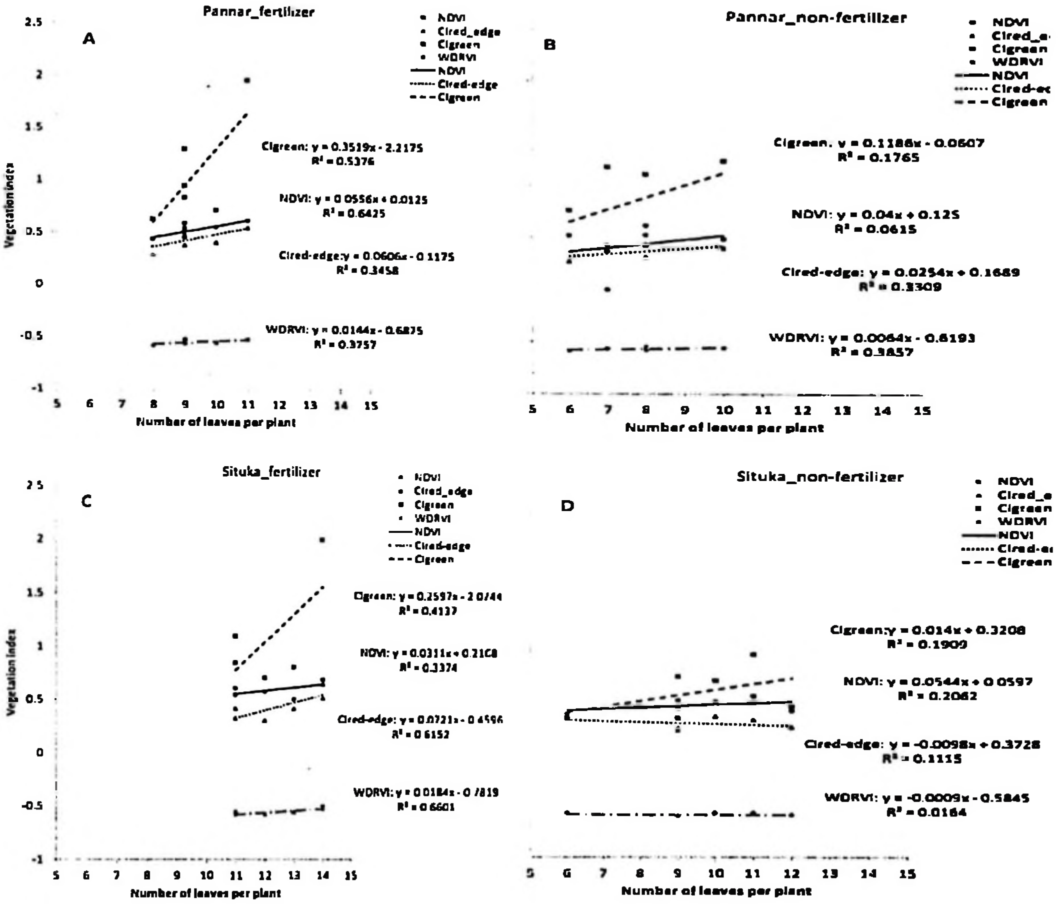

Figure 17: Relationships between number of leaves per plant and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of fertilizer application on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

Under non-fertilizer conditions, the R^2 values were less than 0.40, indicating that as much as 60% or more of the variations in number of leaves per plant for both varieties could not be depicted by the VIs linear function under non-fertilizer conditions. CI_{green} and NDVI performed better for detection of number of leaves per plant for low canopy *Pannar* differently from $CI_{red\text{-}edge}$ and WDRVI which revealed the same for higher canopy *Situka*. CI_{green} showed similar response as NDVI which has been found by previous researches (Mondal *et al.*, 2011; Dempewolf *et al.*, 2013) to perform better under low canopy and saturates at very dense crop canopy, different from what was detected by $CI_{red\text{-}edge}$ and

WDRVI. Thus, CI_{green} and NDVI can be used to estimate of number of leaves per plant for low canopy, similarly $CI_{red\text{-}edge}$ and WDRVI for high canopy maize variety when grown under similar fertilizer conditions.

4.5.3.2 Vegetation indices for detecting the effect of pigeon pea intercropping on number of leaves per plant

Figure 18 (A-D) show that, the number of leaves per plant were best detected by VIs for both maize varieties without pigeon pea intercropping with the R^2 values ranging between 0.61 (*Pannar* CI_{green}) and 0.99 (*Situka* CI_{green}). Figure 18 (A and C) show that the R^2 values were the highest for *Situka* (CI_{green} 0.99, NDVI 0.92, WDRVI 0.91, and $CI_{red\text{-}edge}$ 0.89) compared to *Pannar* (CI_{green} 0.61, NDVI 0.73, WDRVI 0.67, and $CI_{red\text{-}edge}$ 0.69). Similarly, the NDVI (R^2 = 0.85) and CI_{green} (R^2 = 0.65) were the best indices for the detection of the number of leaves per plant for *Pannar* maize variety intercropped with pigeon pea. The variations of number of leaves per plant under pigeon pea conditions can hardly be detected on *Situka* (by all VIs) and *Pannar* (by $CI_{red\text{-}edge}$ and WDRVI) due to small fractions ($R^2 \leq 0.30$) that can be explained by linear relationship functions shown in Figure 18 (B and D). These results reveal that the CI_{green} variations in number of leaves per plant were low *(Pannar)* and high *(Situka)* depicting better performance of *Pannar* than *Situka* maize variety under non-fertilizer conditions.

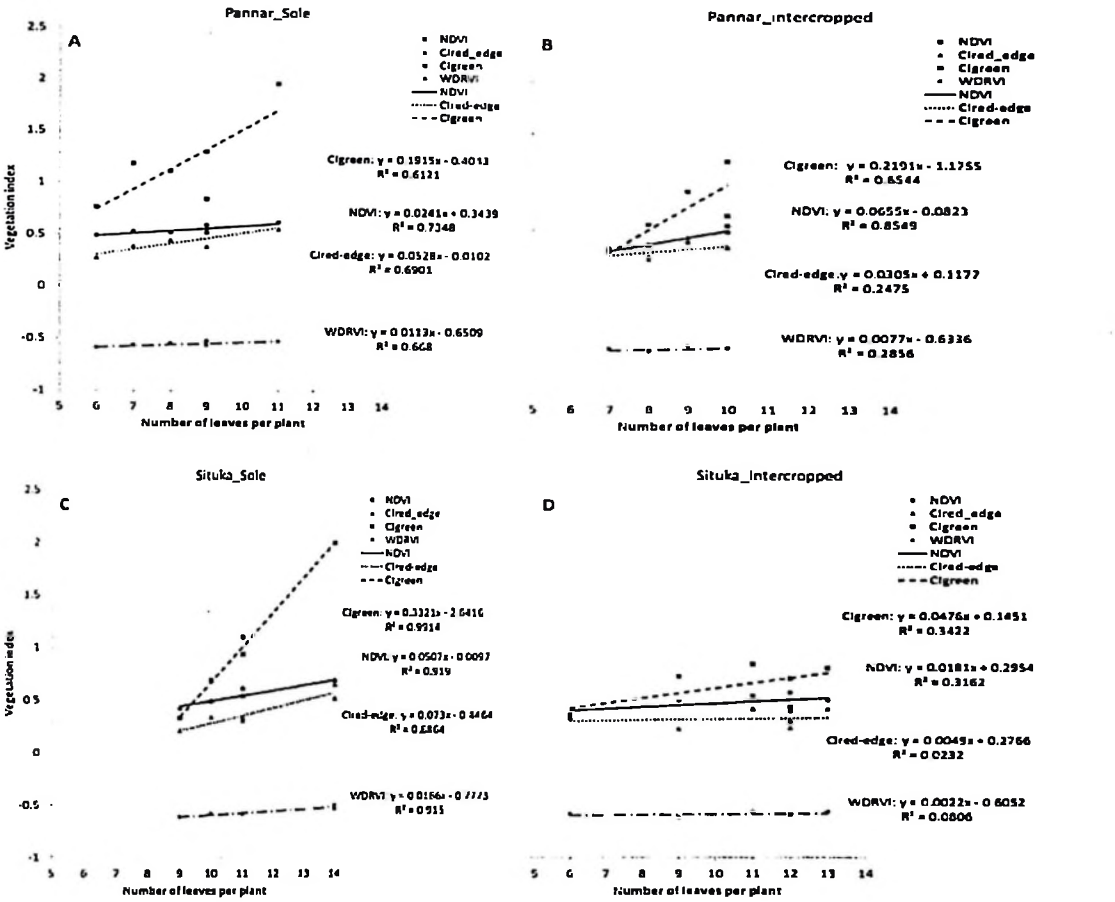

Figure 18: Relationships between number of leaves per plant and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of pigeonpea intercropping on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

The CI_{green} and NDVI were the best indices for detection of the number of leaves per plant for maize under intercropping, indicating high sensitive of these indices on low number of leaves per plant (low canopy cover) probably due to effect of pigeon pea intercrop on maize related with low plant density and low canopy cover caused by nutrient competition (Kimaro *et al.*, 2009; Amare *et al.*, 2012). Lower canopy cover was reported by Liebisch, *el al.* (2015) to affect VIs as information about leaf greenness is masked by differences in canopy cover.

4.5.3.3 Vegetation indices for detecting the effect of fertilizer on maize plant height

Figure 19 (A-D) show linear relationships between plant heights and VIs for *Pannar* and *Situka* maize varieties under the effect of fertilizer application. Figure 19 (A and C) show that the R^2 were higher than 0.50 for *Pannar* plant heights (CI_{green}, $R^2 = 0.66$; NDVI, $R^2 = 0.51$) and *Situka* (CI_{green}, $R^2 = 0.62$). The linear relationship of plant height with VIs under non-fertilizer condition depicted R^2 values for *Situka* CI_{green} (0.66) and NDVI (0.75) than *Pannar*, indicating better detection of *Situka* than *Pannar* plant height as shown in Figure 19 (B and D). The R^2 values for $CI_{red\text{-}edge}$ and WDRVI with plant heights were less than 0.50 indicating that these indices were poor in detection of plant heights under the effect of fertilizer application.

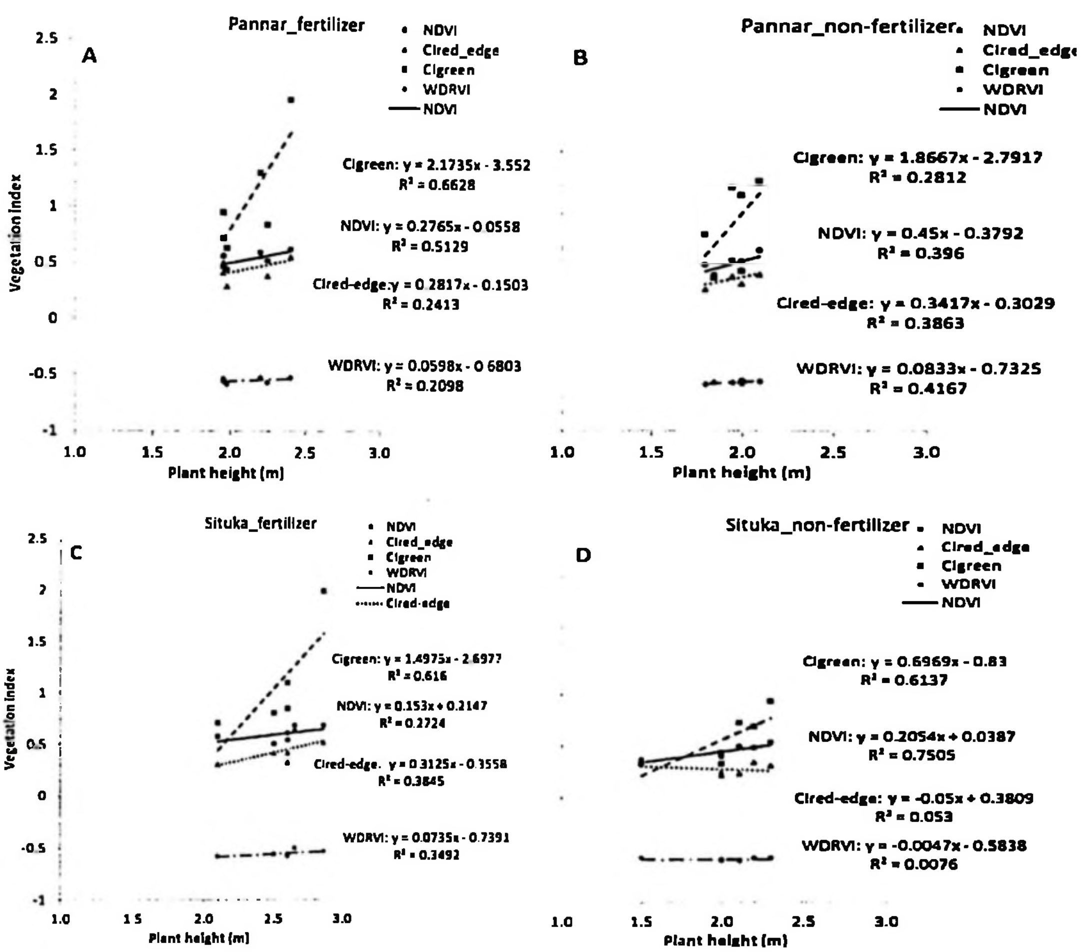

Figure 19: Relationships between plant height and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of fertilizer application on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.5.3.4 Vegetation indices for detecting the effect of pigeon pea intercropping on maize plant height

Evaluation of VIs for the detection of the effect of pigeon pea intercropping on maize plant height is depicted by linear relationship function in Figure 20 (A - D). Figure 20 (A and C) indicate that R^2 values for linear relationship functions between plant height and VIs were greater than 0.50 for maize grown without pigeon pea intercrop except *Pannar* CI_{green} ($R^2 = 0.48$). There were higher R^2 values for *Situka* than those observed on *Pannar* grown without intercropping, whereby $R^2 > 0.90$ were revealed by CI_{green} (0.92) and NDVI (0.95). The R^2 values for $CI_{red\text{-}edge}$ and WDRVI were approximately 0.60 indicating that they are also good detectors of the effect of pigeon pea intercropping on maize height (without intercropping), but with lower precision than NDVI and CI_{green}.

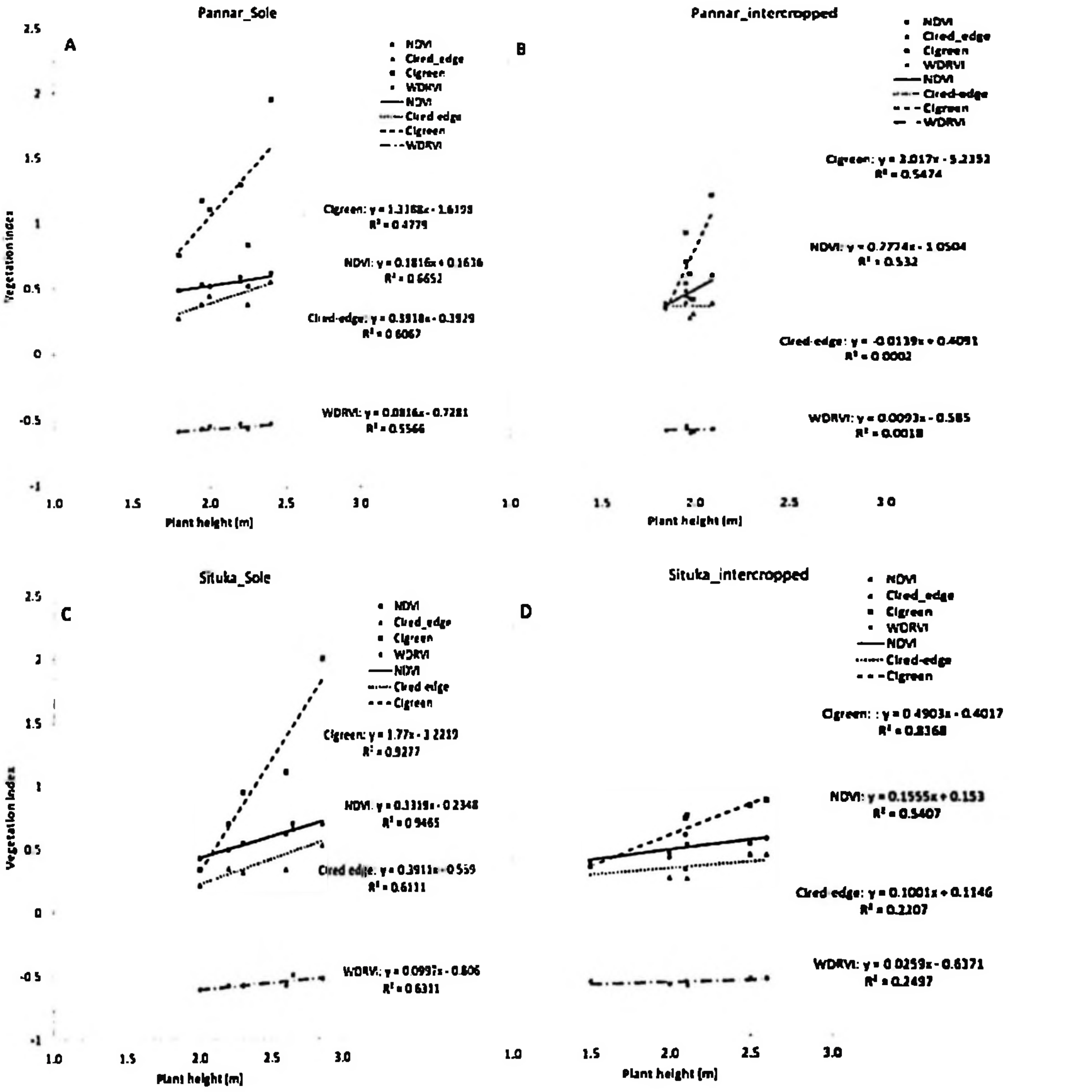

Figure 20: Relationships between plant height and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of pigeonpea intercropping on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.5.3.5 Vegetation indices for detecting the effect of fertilizer application on LAI

The coefficients of determination (R^2) for simple regression models between green LAI and CI_{green}, NDVI, $CI_{red\text{-}edge}$, and WDRVI derived from *Pannar* and *Situka* maize varieties under the effect of fertilizer application are shown in Figure 21(A - D). The relationship between LAI and VIs were generally poor ($R^2 < 0.50$) for all indices tested except CI_{green}. Under fertilizer conditions the R^2 values were 0.56 (*Pannar*) and 0.74 (*Situka*). Under non-fertilizer conditions, the R^2 for CI_{green} was 0.61 (*Pannar*).

Viña *et al.* (2011) found the strong significant linear relationship between $CI_{red\text{-}edge}$ and CI_{green} vs. Green LAI and these indices were sensitive across the entire range of green LAI ($\leq 6\ m^2/m^2$). Their study also noted that CI_{green} and $CI_{red\text{-}edge}$ were the best for detecting green LAI values > 3 m^2/m^2; the NDVI (Green LAI < 2 m^2/m^2), while the WDRVI was found with higher sensitivity than CI_{green} and $CI_{red\text{-}edge}$ at green LAI > 2 m^2/m^2. Results of this study have shown that it's only the CI_{green} which depicted similar results to those observed by Viña *et al.* (2011), thus remained the best index for detection of green LAI within the range of 56 % to 74%.

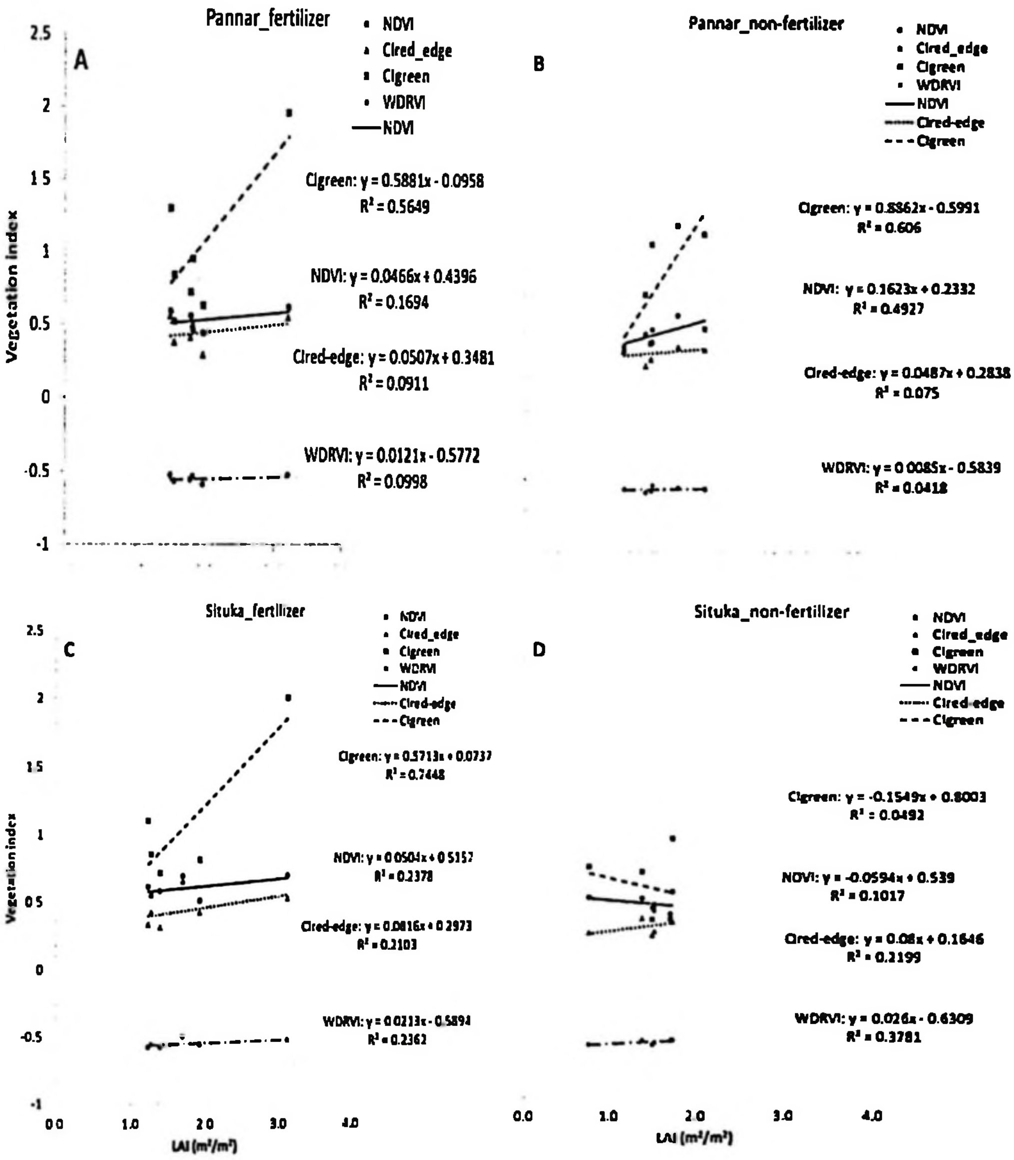

Figure 21: Relationships between LAI and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of fertilizer on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.5.3.6 Vegetation indices for detecting the effect of pigeon pea intercropping on green LAI

Figure 22 shows that the variation of green LAI for the selected window was poorly depicted by the VIs for both *Pannar* and *Situka* maize varieties when intercropped with pigeon pea. The CI_{green} was the only index which was able to explain the observed variations of LAI in a linear regression model at 77 % (R^2 = 0.77) for *Pannar* maize variety grown without intercropping. The R^2 values for the remaining VIs were less than 0.40 except NDVI for *Pannar* without intercropping (R^2 = 0.47) and with intercropping (R^2 = 0.45), meaning that about 60 % of the observed variation in LAI cannot be explained by $CI_{red\text{-}edge}$ and WDRVI in a linear relationship function. CI_{green} has shown a better performance for detection of green LAI for early maturing *Pannar* maize variety under pigeon pea intercropping.

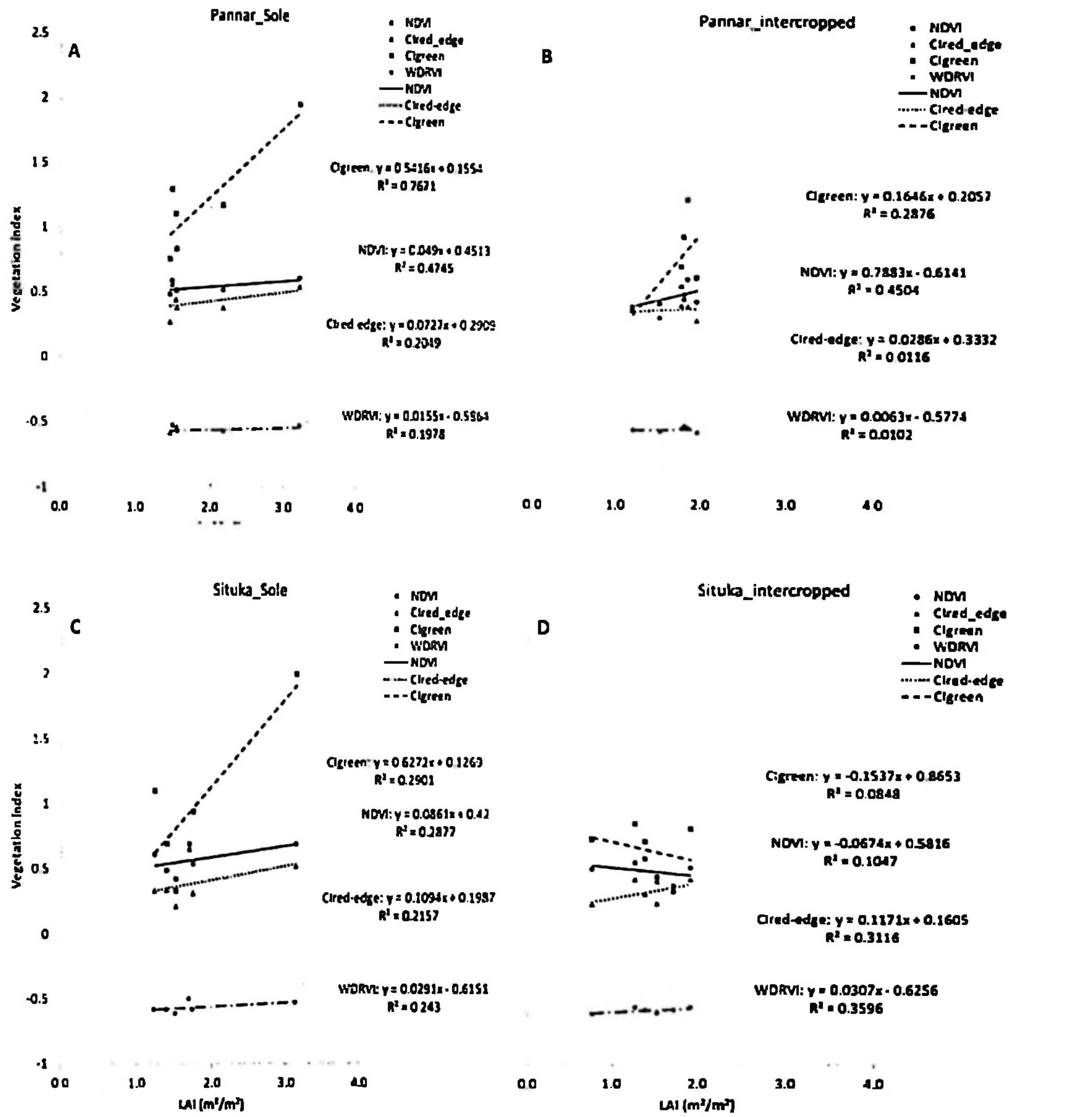

Figure 22: Relationships between LAI and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of pigeon pea intercropping on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.5.3.7 Vegetation indices for detecting the effect of fertilizer application on biomass yield

The strength of the VIs to detect the effect of fertilizer application on biomass revealed low R^2 for both *Pannar* and *Situka* maize varieties with the highest values depicted by CI_{green} on *Pannar* under fertilizer ($R^2 = 0.61$) and on non-fertilizer ($R^2 = 0.73$) condition (Figure 23). If the R^2 value of 0.55 is assumed to be the critical value to determine whether a regression is strong or not in this experiment, the regression of biomass yield with VIs was generally strong for all VIs in fertilized and CI_{green} for non-fertilizer *Pannar* maize variety (Figure 23A and B). None of the R^2 value greater than 0.50 was observed between VIs tested and *Situka* maize variety under fertilizer and non-fertilizer conditions (Figure 23C and D). In spite of the low R^2 values observed on *Situka*, NDVI had the highest R^2 value of 0.42 under non-fertilizer condition.

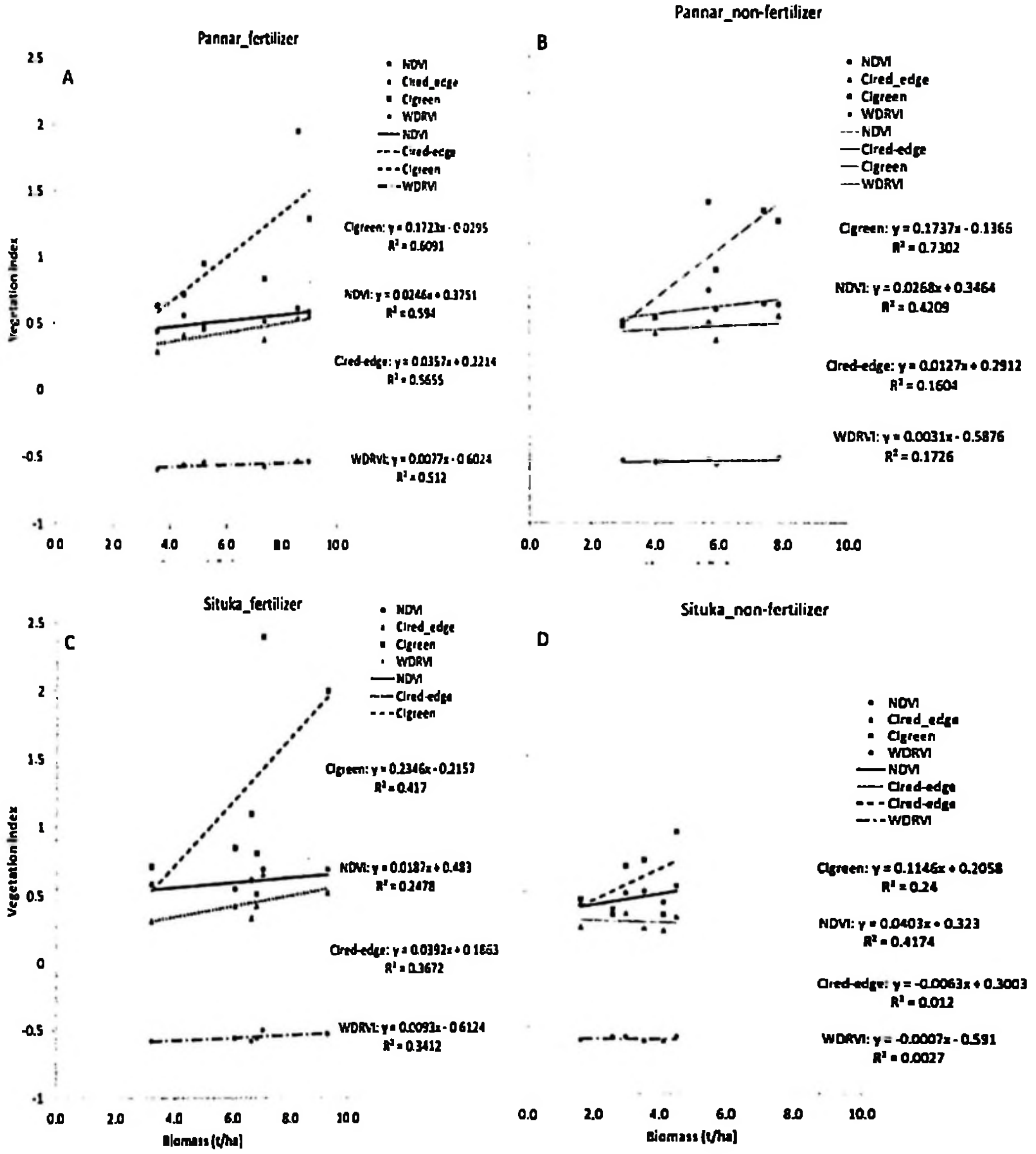

Figure 23: Relationships between biomass and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of fertilizer application on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.5.3.8 Vegetation indices for detecting the effect of intercropping on biomass yield

Figure 24 shows that the regression model for $CI_{red-edge}$ (R^2 = 0.96) and WDRVI (R^2 = 0.94) were the best for detection of biomass for *Pannar* maize variety grown without intercropping, followed by NDVI (R^2 = 0.74), and CI_{green} (R^2 = 0.53). However, under the similar conditions the performance of $CI_{red-edge}$ (R^2 = 0.50), and WDRVI (R^2 = 0.49) for *Situka* were lower compared to NDVI (R^2 = 0.77) and CI_{green} (R^2 = 0.65). The CI_{green} (R^2 = 0.86) was the best index for detection of biomass for *Pannar* under pigeon pea intercropping. The R^2 values for biomass and NDVI was 0.61(intercropped *Pannar*), biomass and CI_{green} and with $CI_{red-edge}$ (R^2 = 0.65, intercropped *Situka*), and WDRVI (R^2 = 0.58, intercropped *Situka*). The performance was poor (R^2 < 0.50) for $CI_{red-edge}$ and WDRVI (*Pannar*) and NDVI (*Situka*) for pigeon pea intercropped maize biomass.

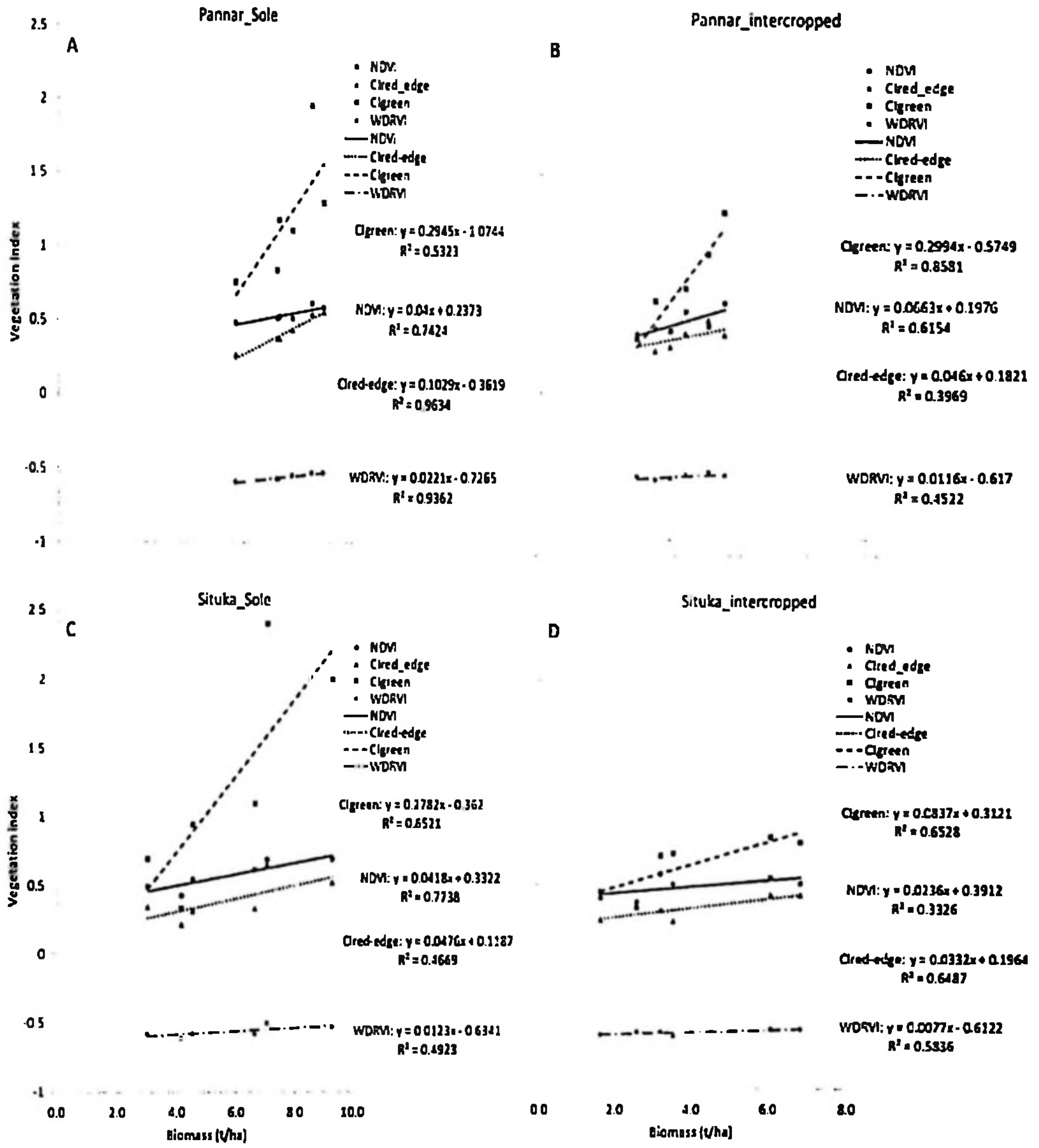

Figure 24: Relationships between biomass and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of pigeon pea intercropping on Pannar (A, B) and Situka (C, D) maize varieties.

4.5.3.9 Vegetation indices for detecting the effect of fertilizer application of Maize grain yield

Figure 25 show the performance of VIs for detection of maize grain yield influenced by fertilizer application on *Pannar* and *Situka* maize varieties. The variation of grain yield with fertilizer application on maize was better explained by CI_{green} and NDVI for both varieties under fertilizer (Figure 25A and C) and non-fertilizer (Figure 25B and D) conditions. The highest R-squared values were observed on non-fertilized *Pannar* (CI_{green}, $R^2 = 0.91$) and *Situka* (NDVI, $R^2 = 0.76$). However, r-squared were above 0.50 under fertilizer conditions for *Pannar* (CI_{green} $R^2 = 0.76$; NDVI, $R^2 = 0.69$; $CI_{red-edge}$, $R^2 = 0.61$; and WDRVI, $R^2 = 0.56$) and *Situka* (CI_{green} $R^2 = 0.68$; NDVI, $R^2 = 0.54$; $CI_{red-edge}$, $R^2 = 0.56$; and WDRVI, $R^2 = 0.56$).

Under non-fertilizer conditions, the NDVI ($R^2 = 0.62$) was better after CI_{green} ($R^2 = 0.91$) for *Pannar* and CI_{green} ($R^2 = 0.53$) was better after NDVI ($R^2 = 0.76$) for *Situka* maize variety. Variations of grain yields for non-fertilized maize could not be explained by $CI_{red-edge}$ and WDRVI linear function due to the lowest values reported in Figure 25B (*Pannar*, $R^2 < 0.30$) and Figure 25D (*Situka*, $R^2 = 0.00$).

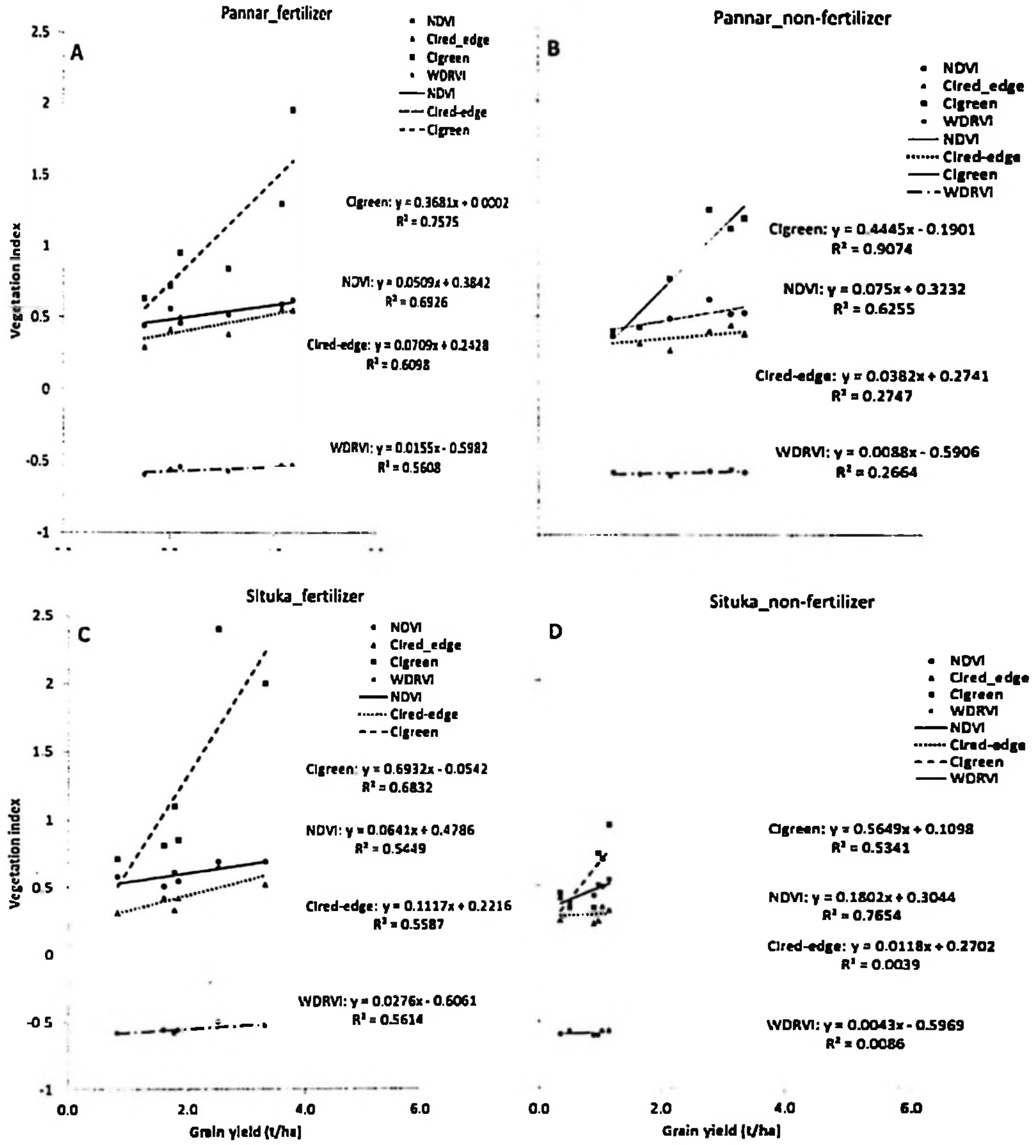

Figure 25: Relationships between grain yield and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of fertilizer application on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.5.3.10 Vegetation indices for detecting the effect of intercropping on Maize grain yield

Performance of VIs for detection of maize grain yield for *Pannar* and *Situka* maize varieties grown with and without pigeon pea intercrop. The R^2 values were higher for both *Pannar* and *Situka* without intercropping than when intercropped with pigeon pea, while *Pannar* depicted the highest values (Figure 26). Through linear relationship function, these indices were able to explain about 70 to 90% of the variations in yields for *Pannar* (Figure 26A) and 68 to 84% for *Situka* maize variety (Figure 26C) without intercropping. The higher R^2 values observed on sole *Pannar (*NDVI 0.93; $CI_{red\text{-}edge}$ 0.92, and WDRVI 0.86), and sole *Situka* (NDVI 0.84; CI_{green} 0.80) revealed the best detection capability of these indices for sole maize grain yields.

Under pigeon pea intercropping, the R^2 values were higher for *Pannar* (NDVI 0.76, and CI_{green} 0.92) than *Situka* (NDVI 0.62 and CI_{green} 0.76). About more than 50% of the variations in grain yields for maize intercropped with pigeon pea could not be explained by $CI_{red\text{-}edge}$ and WDRVI with a linear relationship function ($R^2 < 0.55$). This is probably due high variation of maize crop conditions and low yields under intercropping.

Previous research indicate that intercropping of pigeon pea in association with maize results in significant reduction of maize yield (Karnataka *et al.*, 2007), due to competitive ability of pigeon pea in the face of maize crop (Kimaro *et al.*, 2009; Amare *et al.*, 2012); and it's was susceptible to water logging (Sheahan, 2012) associated to excessive rains.

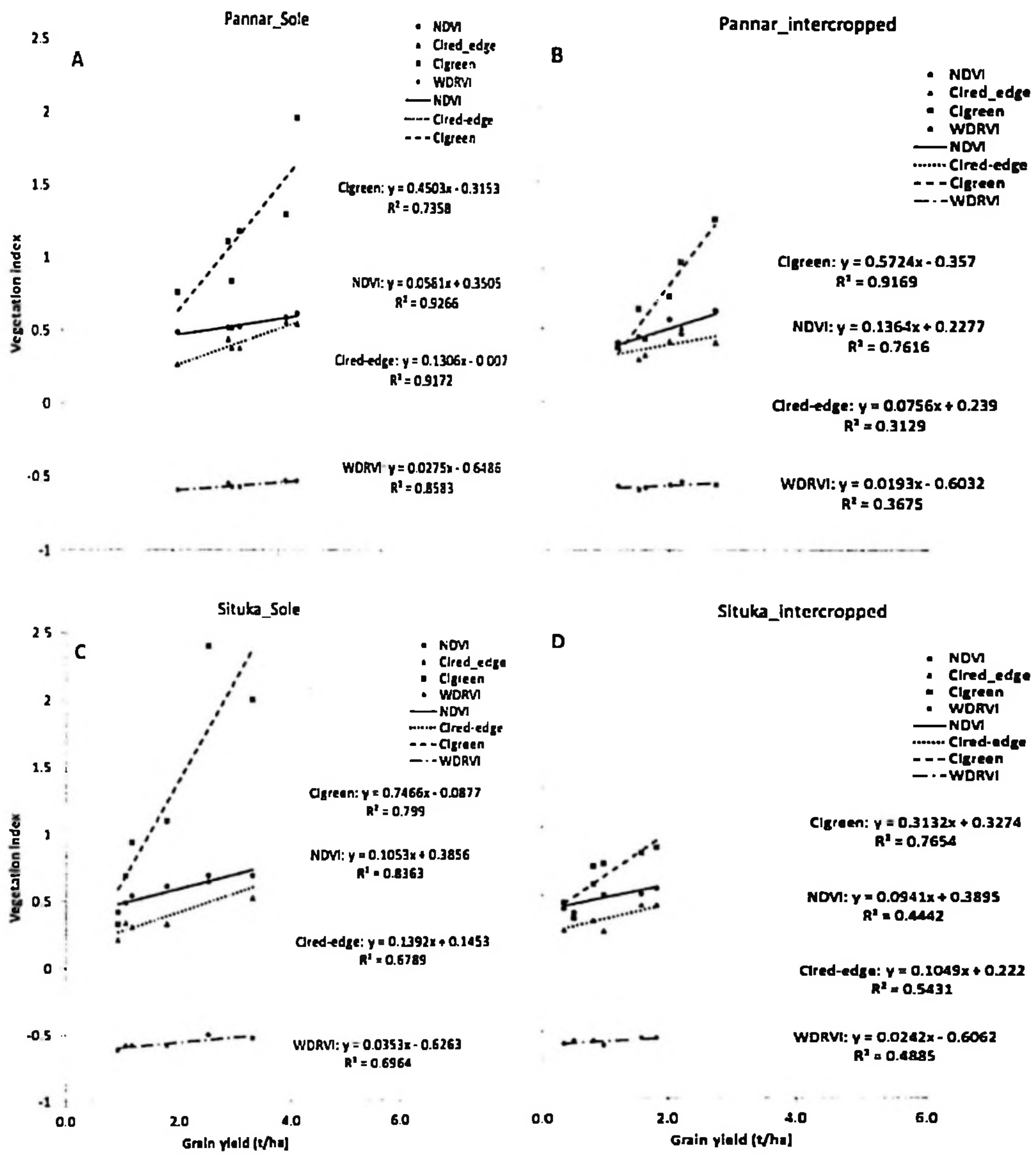

Figure 26: Relationships between grain yield and NDVI, $CI_{red\text{-}edge}$, CI_{green}, and WDRVI for the detection of the effect of pigeon pea intercropping on *Pannar* (A, B) and *Situka* (C, D) maize varieties.

4.6 The usefulness of coarse satellite images for monitoring maize crop condition and yields

4.6.1 Assessment of cloud cover

Cloud cover (%) was computed from 10 km by 10 km and 1 km by 1 km rectangular polygons enclosing the study areas. Table 12 highlights the effect of cloud cover for the quality of Landsat 8 images to be used for monitoring crop growth condition and yield over the study area during the main growing season March – May. The results show that percentage cloud cover was increasing from start of the season in March reaching highest peak for a scene collected on 22 April 2016. The 95.1 % and 83.7 % cloud cover were observed over 10 km by 10 km and 1 km by 1 km polygons, respectively. Furthermore, results show that on 6 April (8.8 %), 24 May (0.0 %), and 9 June 2016 (10.3 %) for the 1 km x 1 km polygon, thus they were useful for computation of vegetation indices important for monitoring crop condition and yield. These results show that at critical maize growth stages in April and May 2016 the Landsat 8 imagery collected were less useful for monitoring crops over the large area within 10 km by 10 km rectangular polygon due to higher percentages of cloud cover depicted in the season.

Table 12: Cloud covers assessment of Landsat 8 scenes collected during the crop growing season March to June 2016

Acquisition date	Landsat scene ID	Cloud cover (%)		
		Entire scene	10 km x 10 km	1km x1km
21 March	LC81670652016081LGN00	28.2	49.3	61.1
6 April	LC81670652016097LGN00	68.3	78.9	8.8
22 April	LC81670652016113LGN00	60.7	95.1	83.7
8 May	LC81670652016129LGN00	5.3	59.9	47.1
24 May	LC81670652016145LGN00	3.9	4.4	0.00
9 June	LC81670652016161LGN00	7.7	58.0	10.3

4.6.2 Effect of cloud cover on satellite and UAV derived indices

Time series analysis of NDVI, CI_{green}, and WDRVI computed for the different maize fields (Figure 27) shows that both Landsat 8 and UAV depicted low VIs on 21 March and 6 April, 2016 on Field 1 as shown in Figure 27(a-c). Figure 27(a-f), the UAV derived VIs were higher than those obtained from Landsat 8 throughout the season except CI_{green} which depicted different pattern on 6^{th} April and 9 June (Field 1) and 6 April and 24 May (Field 2). Both UAV and Landsat 8 derived VIs depicted increasing trend till 6 April for Field 1 as shown in Figure 27(a-c), the pattern which was maintained in Field 2 by Landsat 8 while UAV-VIs decreasing (Figure 27e-f). Field 1 had lower UAV-VIs than Field 2 values at the beginning indicating different crop stages where at field 1 the crop was at early development stages and Field 2 was at more advanced growth stages. There was large decrease in UAV-VIs on 6 April for Field 2 (Figure 27d-f), slightly depicted by CI_{green} (Figure 27b) where such brief decrease in UAV- and increase in Landsat 8 – VIs probably was due to factors other than normal crop senescence.

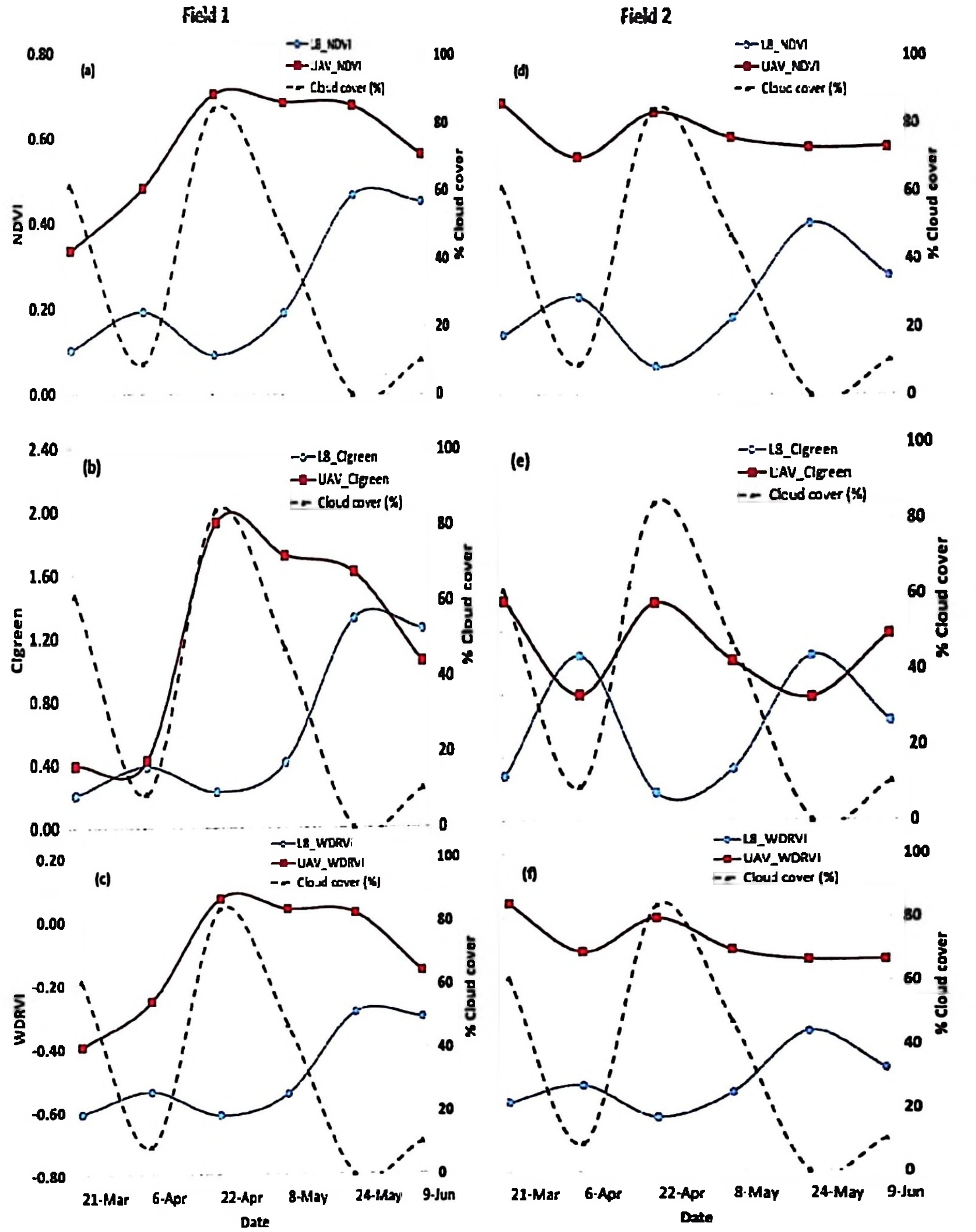

Figure 27: The effect of cloud cover on Landsat 8 and UAV derived vegetation indices. A vegetation index for a date is the average of each field.

The UAV detected peak (maxima) and Landsat 8 (minima) VIs values on 22 April, where the highest VIs at Field 1 were; NDVI (0.70), CI_{green} (1.90), and WDRVI (0.10). Similarly, on 22 April, the Field 2, UAV-VIs values were; NDVI (0.80), CI_{green} (1.40), and WDRVI (0.00). Landsat 8 on the other hand, exhibited the lowest VIs on 22 April for both Field 1 and Field 2. The Landsat 8-VIs on 22 April were about 0.10 (NDVI), 0.20 (CI_{green}), and -0.60 (WDRVI) for Field 1 and Field 2. The maximum peak values for Landsat 8 –VIs were observed one month later on 24 May 2016; as depicted on Field 1 (NDVI (0.50), CI_{green} (1.30), and WDRVI (-0.30)) and Field 2 (NDVI (0.40), CI_{green} (1.00), and WDRVI (-0.40)).

There was negative response of Landsat 8 - VIs on cloud cover. Landsat 8 - VIs run in opposite phases with percentage cloud cover whereby the VIs increased at decreased cloud cover. Although the effect of cloud cover on UAV-VIs was not apparent as it was for Landsat 8 (Figure 27(a–c) vs. (d-f)), but the relationship indicated by these indices in (Figure 27d–f) reveals some positive response of these indices on cloud cover. The effect of cloud cover could be related with changes depicted by all indices in Field 2 on 6 April (Figure 27d-f), while more response observed on CI_{green} (Figure 27e). This was true for both fields and at all phases. However, the minimum Landsat 8-VIs values depicted in April were unlikely because the crop was at full vegetative stage, therefore it could be related with the highest cloud cover reported in the previous section. This is consistent with Hallhan and Preppemeau (2013) who reported that cloud cover is not only visually obstructive of the ground but also introduces error in VIs products. The results show that the satellite underestimate VIs as depicted throughout by time series analysis and large differences between UAV-VIs during maximum cloud cover. The VIs values have shown temporal mismatch between Landsat 8 and UAV- derived values from the beginning of the season, indicating that the observed late peak for Landsat 8 may not be justified because of the effect of cloud on satellite derived indices reported in this work. Cloud cover has been reported to influence the quality of satellite data (Guindin-Garcia (2010) cited Chen *et al.* (2003) as a result of cloud contamination and atmospheric composition.

4.6.3 Comparison of VIs derived from fine (UAV) and coarse (satellite) resolution images

Comparison results for field mean VIs indicated that there was very strong significant difference ($p<0.001$) between UAV and Landsat 8 derived indices for both Field 1 and Field 2 (Table 13), except CI_{green} whose strength was reduced to $p<0.01$ at Field 2 (Table 13B). The CI_{green} exhibited the largest mean difference ($d = 0.55$), variance (0.601), and standard error of the mean (0.129) for Field 1 (Table 13A), similarly under Field 2, mean difference ($d = 0.51$), variance (0.500), and standard error of the mean (0.166) (see Table 13B). The largest mean difference observed can be related to higher values depicted by CI_{green} compared to other indices. However, the large variances and standard error, and small t-values imply small means of the differences resulted from small differences between UAV and Landsat 8 derived CI_{green}. Although all indices depicted significant difference between UAV and Landsat 8 derived VIs ($p<0.01$), the t-values computed for CI_{green} were smaller (d.f 35, $t =4.30$; and d.f 17, $t = 3.06$) than NDVI (d.f 35, $t = 9.75$; and d.f 17, $t = 9.86$) and WDRV (d.f 35, $t = 9.70$; and d.f 17, $t = 9.28$) implying marginal significance for CI_{green} (Table 13).

Table 13: Comparison test for Landsat 8 and UAV vegetation indices at farmer's field conditions

(A) Field 1

Difference between Landsat 8 and UAV-VIs	Mean Difference (d)	Variance	Standard error	t -value	d.f	p-value
NDVI	0.32	0.040	0.033	9.75	35	< 0.001
CI_{green}	0.55	0.601	0.129	4.30	35	< 0.001
WDRVI	0.37	0.052	0.038	9.70	35	< 0.001
(B) Field 2						
NDVI	0.40	0.03	0.040	9.86	17	< 0.001
CI_{green}	0.51	0.500	0.166	3.06	17	0.007
WDRVI	0.45	0.042	0.048	9.28	17	< 0.001

d.f = degrees of freedom

The significance of the difference between UAV and Landsat 8 – VIs varied with day of observation (Table 14). There was a significant difference ($p<0.05$) between UAV and Landsat 8 - NDVI and WDRVI for all observation dates (21 March – 9 June). The strength of the significance were higher with NDVI, followed by WDRVI while CI_{green} depicting significances ($p<0.001$) at marginal t-values (on 22 April and 8 May) and non-significant ($p>0.05$) values for the rest of the season (Table 14). These results indicate that on 22 April and 8 May was the period for maximum differentiations between UAV and Landsat 8 - VIs, probably due to peak cloud cover effect on these indices. On the other hand, the statistical differences between VIs from sensor onboard UAV and Landsat 8 will not be a fixed relationship because reflected sunlight may be different at sometimes based on sun angle, atmospheric conditions and cloud cover.

Table 14: Comparison test for Landsat 8 and UAV vegetation indices based on observation date

Date	Landsat 8 and UAV (Difference)	Mean difference (d)	Variance	Standard error	t -value	p-value
	NDVI	0.34	0.05	0.077	4.35	0.002
21 Mar	CI_{green}	0.50	0.57	0.251	1.97	**0.084**
	WDRVI	0.35	0.086	0.098	3.58	0.007
	NDVI	0.30	0.025	0.052	5.76	< 0.001
6 Apr	CI_{green}	-0.05	0.050	0.074	0.75	**0.473**
	WDRVI	0.33	0.054	0.078	4.23	0.003
	NDVI	0.61	0.001	0.011	56.62	< 0.001
22 Apr	CI_{green}	1.54	0.169	0.137	11.24	< 0.001
	WDRVI	0.66	0.003	0.020	33.75	< 0.001
	NDVI	0.47	0.001	0.013	35.75	< 0.001
8 May	CI_{green}	1.10	0.141	0.125	8.80	< 0.001
	WDRVI	0.54	0.005	0.023	22.83	< 0.001
	NDVI	0.20	0.001	0.010	19.13	< 0.001
24 May	CI_{green}	0.11	0.161	0.134	0.82	**0.437**
	WDRVI	0.28	0.003	0.020	14.52	< 0.001
	NDVI	0.18	0.010	0.034	5.19	< 0.001
9 Jun	CI_{green}	0.04	0.237	0.162	0.28	**0.788**
	WDRVI	0.21	0.012	0.037	5.74	< 0.001

Analysis is based on two-sample t-test (paired) for all nine plots. Bolded p-values ($p > 0.05$) are not significant at 5% probability level.

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study used plant condition parameters to evaluate vegetation indices derived from high resolution sensors for their capability to detect the effect of pigeon pea intercropping and fertilizer application on maize condition and yield characteristics. Plant condition and crop yield parameters such as number of leaves per plant, plant height, LAI, biomass and grain yields improved significantly under fertilized and monocrop maize. These crop condition and yield parameters were significantly reduced under pigeon pea intercropping and non-fertilizer conditions. Variation of CWSI was not significant for differentiating the effect of fertilizer and pigeon pea intercrop on both *Pannar* and *Situka* maize varieties, probably due to plenty of rainfall experienced during the season impeding the index as it works better under water stress conditions. Vegetation indices values between the monocrop maize with fertilizer and intercropped maize-pigeon pea were significantly higher. This was true for both *Pannar* and *Situka* maize varieties. The CI_{green} and NDVI have shown ability to detect differences in maize crop conditions and yields with CI_{green} performing better than the other indices. Of the three indices evaluated for the usefulness of satellite remote sensing VIs, the NDVI and WDRVI derived from UAV and Landsat 8 were significantly different, unlike UAV-CI_{green} which exhibited some consistence with Landsat 8-CI_{green}, and their differences were not statistically significant except under heavy cloud cover. Landsat 8 imagery collected between March and May 2016 were less useful for monitoring crop conditions over the large area due to higher percentages of cloud cover depicted in the season.

5.2 Recommendations

The author recommends for the use of CI_{green} and NDVI to monitor maize condition and yields under mixed farming and fertilizer application practices. However, more investigation is required to test their efficacy under varied agro-ecological conditions and the use of remote sensing sensors that are not affected by cloud cover, e.g. radar, for monitoring maize conditions and yields over large area.

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APPENDICES

Appendix 1: Maize biomass data

Treatment/ replication	Moisture (%)	Moisture content biomass (g)	Dry biomass (g)	Total biomass 10 plants (g)	Harvest index	Biomass kg/ha
T1/1	37.2	1414.7	2385.3	3641.5	4.5	25571.3
T1/2	47.7	1192.4	1307.6	2440.8	6.6	15813.4
T1/3	41.4	1325.8	1874.2	2581.9	6.2	14636.7
T2/1	43.2	971.1	1278.9	2591.5	6.9	47594.8
T2/2	31.2	624.3	1375.7	2586.0	6.9	44677.3
T2/3	31.9	605.8	1294.2	2241.3	7.9	26634.4
T3/1	28.9	1040.0	2560.0	3719.2	4.7	34135.7
T3/2	24.6	590.8	1809.2	3102.3	5.3	34336.1
T3/3	14.3	557.9	3342.1	5204.2	2.9	28097.4
T4/1	39.8	1034.4	1565.6	2163.3	7.2	7018.0
T4/2	34.1	1262.4	2437.6	3810.2	3.8	25714.1
T4/3	24.2	1159.9	3640.1	5017.8	3.2	10852.2
T5/1	33.3	599.2	1200.8	2590.2	7.0	28668.0
T5/2	22.0	418.4	1481.6	2937.3	6.2	35698.6
T5/3	30.8	615.3	1384.7	2808.1	6.5	23499.8
T6/1	36.4	1165.8	2034.2	3793.1	4.5	73724.9
T6/2	40.8	1550.2	2249.8	4178.5	4.0	63167.3
T6/3	19.2	769.2	3230.8	4765.2	3.4	52741.1
T7/1	17.6	229.3	1070.7	2520.4	7.3	59901.9
T7/2	36.7	661.4	1138.6	2453.8	7.5	55641.2
T7/3	29.2	555.5	1344.5	2667.6	6.8	46086.8
T8/1	21.6	344.9	1255.1	2901.0	6.2	43854.4
T8/2	28.3	480.5	1219.5	2315.0	7.7	21247.7
T8/3	25.9	388.8	1111.2	2109.7	8.4	14237.8

Appendix 2: Maize biomass computation

Treatment/ replication	Moisture (%)	Moisture content biomass (g)	Dry biomass (g)	Total biomass 10 plants (g)	Harvest index	Biomass kg/ha
T1/1	37.2	1414.7	2385.3	3641.5	4.5	25571.3
T1/2	47.7	1192.4	1307.6	2440.8	6.6	15813.4
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T3/2	24.6	590.8	1809.2	3102.3	5.3	34336.1
T3/3	14.3	557.9	3342.1	5204.2	2.9	28097.4
T4/1	39.8	1034.4	1565.6	2163.3	7.2	7018.0
T4/2	34.1	1262.4	2437.6	3810.2	3.8	25714.1
T4/3	24.2	1159.9	3640.1	5017.8	3.2	10852.2
T5/1	33.3	599.2	1200.8	2590.2	7.0	28668.0
T5/2	22.0	418.4	1481.6	2937.3	6.2	35698.6
T5/3	30.8	615.3	1384.7	2808.1	6.5	23499.8
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T6/2	40.8	1550.2	2249.8	4178.5	4.0	63167.3
T6/3	19.2	769.2	3230.8	4765.2	3.4	52741.1
T7/1	17.6	229.3	1070.7	2520.4	7.3	59901.9
T7/2	36.7	661.4	1138.6	2453.8	7.5	55641.2
T7/3	29.2	555.5	1344.5	2667.6	6.8	46086.8
T8/1	21.6	344.9	1255.1	2901.0	6.2	43854.4
T8/2	28.3	480.5	1219.5	2315.0	7.7	21247.7
T8/3	25.9	388.8	1111.2	2109.7	8.4	14237.8

Appendix 3: Maize Yield data

Treatment/ replication	Area m²	Moisture (%)	Moisture content grain(g)	Dry yield (kg/ha)	Maize yield at 12% moisture moisture (kg/ha)	Number of grains per m²	Harvest index	Biomass yield (kg/ha)	Residue & cob yield (kg/ha)
T1/1	9	0.20	259.12	1156.5	1314.2	338.17	4.52	25571.26	24414.72
T1/2	9	0.21	257.14	1047.6	1190.5	302.78	6.62	15813.43	14765.82
T1/3	9	0.22	230.61	910.4	1034.6	295.12	6.22	14636.69	13726.26
T2/1	9	0.13	449.59	3278.2	3725.3	964.19	6.89	47594.85	44316.61
T2/2	9	0.14	443.15	3063.2	3480.9	805.04	6.86	44677.35	41614.18
T2/3	9	0.14	302.67	2108.1	2395.6	598.05	7.92	26634.43	24526.29
T3/1	9	0.16	269.29	1589.7	1806.5	483.18	4.66	34135.70	32546.03
T3/2	9	0.20	402.43	1830.6	2080.3	490.79	5.33	34336.09	32505.46
T3/3	9	0.26	262.39	819.6	931.3	226.71	2.92	28097.43	27277.86
T4/1	9	0.24	142.48	508.4	577.7	151.75	7.24	7017.95	6509.60
T4/2	9	0.29	363.82	984.6	1118.9	274.66	3.83	25714.08	24729.44
T4/3	9	0.21	83.70	351.4	399.4	112.28	3.24	10852.16	10500.71
T5/1	9	0.11	231.10	2021.0	2296.6	579.08	7.05	28667.95	26646.95
T5/2	9	0.12	264.71	2205.9	2506.7	600.24	6.18	35698.62	33492.73
T5/3	9	0.11	173.98	1528.9	1737.4	420.03	6.51	23499.79	21970.88
T6/1	9	0.17	626.24	3304.2	3754.7	968.97	4.48	73724.89	70420.71
T6/2	9	0.19	542.86	2507.9	2849.9	687.11	3.97	63167.34	60659.40
T6/3	9	0.22	457.22	1769.8	2011.1	512.97	3.36	52741.12	50971.36
T7/1	9	0.11	477.01	4358.9	4953.3	1107.72	7.28	59901.85	55542.97
T7/2	9	0.11	467.35	4147.4	4712.9	1075.85	7.45	55641.20	51493.81
T7/3	9	0.12	388.73	3123.6	3549.6	861.69	6.78	46086.77	42963.13
T8/1	9	0.12	337.41	2736.2	3109.3	666.55	6.24	43854.44	41118.23
T8/2	9	0.14	232.94	1630.1	1852.3	457.24	7.67	21247.70	19617.64
T8/3	9	0.14	168.85	1201.3	1365.1	424.18	8.44	14237.80	13036.52

Appendix 4: Maize yield computation

Treatment/ replication	Area m²	Moisture (%)	Moisture content grain(g)	Dry yield (kg/ha)	Maize yield at 12% moisture moisture (kg/ha)	Number of grains per m²	Harvest index	Biomass yield (kg/ha)	Residue & cob yield (kg/ha)
T1/1	9	0.20	259.12	1156.5	1314.2	338.17	4.52	25571.26	24414.72
T1/2	9	0.21	257.14	1047.6	1190.5	302.78	6.62	15813.43	14765.82
T1/3	9	0.22	230.61	910.4	1034.6	295.12	6.22	14636.69	13726.26
T2/1	9	0.13	449.59	3278.2	3725.3	964.19	6.89	47594.85	44316.61
T2/2	9	0.14	443.15	3063.2	3480.9	805.04	6.86	44677.35	41614.18
T2/3	9	0.14	302.67	2108.1	2395.6	598.05	7.92	26634.43	24526.29
T3/1	9	0.16	269.29	1589.7	1806.5	483.18	4.66	34135.70	32546.03
T3/2	9	0.20	402.43	1830.6	2080.3	490.79	5.33	34336.09	32505.46
T3/3	9	0.26	262.39	819.6	931.3	226.71	2.92	28097.43	27277.86
T4/1	9	0.24	142.48	508.4	577.7	151.75	7.24	7017.95	6509.60
T4/2	9	0.29	363.82	984.6	1118.9	274.66	3.83	25714.08	24729.44
T4/3	9	0.21	83.70	351.4	399.4	112.28	3.24	10852.16	10500.71
T5/1	9	0.11	231.10	2021.0	2296.6	579.08	7.05	28667.95	26646.95
T5/2	9	0.12	264.71	2205.9	2506.7	600.24	6.18	35698.62	33492.73
T5/3	9	0.11	173.98	1528.9	1737.4	420.03	6.51	23499.79	21970.88
T6/1	9	0.17	626.24	3304.2	3754.7	968.97	4.48	73724.89	70420.71
T6/2	9	0.19	542.86	2507.9	2849.9	687.11	3.97	63167.34	60659.40
T6/3	9	0.22	457.22	1769.8	2011.1	512.97	3.36	52741.12	50971.36
T7/1	9	0.11	477.01	4358.9	4953.3	1107.72	7.28	59901.85	55542.97
T7/2	9	0.11	467.35	4147.4	4712.9	1075.85	7.45	55641.20	51493.81
T7/3	9	0.12	388.73	3123.6	3549.6	861.69	6.78	46086.77	42963.13
T8/1	9	0.12	337.41	2736.2	3109.3	666.55	6.24	43854.44	41118.23
T8/2	9	0.14	232.94	1630.1	1852.3	457.24	7.67	21247.70	19617.64
T8/3	9	0.14	168.85	1201.3	1365.1	424.18	8.44	14237.80	13036.52

Appendix 5: Biomass and grain yields comparisons for Pannar and Situka maize varieties the differences among different treatments

Comparison	Grain yield (t/ha)		Biomass (t/ha)	
	Difference	Significant	Difference	Significant
Pannar No Pigeonpea Fertilizer vs Pannar -No Pigeonpea No fertilizer	1.06	yes	1.21	no
Pannar No Pigeonpea Fertilizer vs Situka No Pigeonpea Fertilizer	1.35	yes	0.64	no
Pannar No Pigeonpea Fertilizer vs Pannar Pigeonpea Fertilizer	1.96	yes	3.87	yes
Pannar No Pigeonpea Fertilizer vs Pannar Pigeonpea No fertilizer	2.02	yes	4.05	yes
Pannar No Pigeonpea Fertilizer vs Situka Pigeonpea Fertilizer	2.46	yes	2.93	yes
Pannar No Pigeonpea Fertilizer vs Situka No Pigeonpea No fertilizer	2.84	yes	4.41	yes
Pannar No Pigeonpea Fertilizer vs Situka Pigeonpea No fertilizer	3.26	yes	5.71	yes
Pannar No Pigeonpea No fertilizer vs Situka No Pigeonpea Fertilizer	0.29	no	-0.56	no
Pannar No Pigeonpea No fertilizer vs Pannar Pigeonpea Fertilizer	0.90	no	2.67	yes
Pannar No Pigeonpea No fertilizer vs Pannar Pigeonpea No fertilizer	0.96	no	2.85	yes
Pannar No Pigeonpea No fertilizer vs Situka Pigeonpea Fertilizer	1.40	yes	1.72	no
Pannar No Pigeonpea No fertilizer vs Situka No Pigeonpea No fertilizer	1.78	yes	3.21	yes
Pannar No Pigeonpea No fertilizer vs Situka Pigeonpea No fertilizer	2.20	yes	4.50	yes
Pannar Pigeonpea Fertilizer vs Pannar Pigeonpea No fertilizer	0.06	no	0.18	no
Pannar Pigeonpea Fertilizer vs Situka Pigeonpea Fertilizer	0.51	no	-0.94	no
Pannar Pigeonpea Fertilizer vs Situka No Pigeonpea No fertilizer	0.88	no	0.54	no
Pannar Pigeonpea Fertilizer vs Situka Pigeonpea No fertilizer	1.30	yes	1.84	no
Pannar Pigeonpea No fertilizer vs Situka Pigeonpea Fertilizer	0.44	no	-1.12	no
Pannar Pigeonpea No fertilizer vs Situka No Pigeonpea No fertilizer	0.82	no	0.36	no
Pannar Pigeonpea No fertilizer vs Situka Pigeonpea No fertilizer	1.24	yes	1.66	no
Situka No Pigeonpea Fertilizer vs Pannar Pigeonpea Fertilizer	0.61	no	3.23	yes
Situka No Pigeonpea Fertilizer vs Pannar Pigeonpea No fertilizer	0.67	no	3.41	yes
Situka No Pigeonpea Fertilizer vs Situka Pigeonpea Fertilizer	1.11	yes	2.29	no
Situka No Pigeonpea Fertilizer vs Situka No Pigeonpea No fertilizer	1.49	yes	3.77	yes
Situka No Pigeonpea Fertilizer vs Situka Pigeonpea No fertilizer	1.91	yes	5.07	yes
Situka Pigeonpea Fertilizer vs Situka No Pigeonpea No fertilizer	0.38	no	1.48	no
Situka Pigeonpea Fertilizer vs Situka Pigeonpea No fertilizer	0.80	no	2.78	yes
Situka No Pigeonpea No fertilizer vs Situka Pigeonpea No fertilizer	0.42	no	1.30	no

Appendix 6: Data and work flow chart